

Sectoral Transport Mode Elasticities and International Trade

Jeong-won Ko* Sergey Nigai[†] Alec Truax[‡]

September, 2026

Abstract

We estimate sector-specific transport-mode elasticities in international trade costs using newly available bilateral trade data disaggregated by mode and sector for 2016–2025. We rely on an instrumental-variable approach that exploits the interaction of global, mode-specific cost shocks with exogenous bilateral geography to identify elasticities for 21 manufacturing sectors. Our estimates reveal substantial heterogeneity, ranging from statistically insignificant values near zero to 12.1, with high value-to-weight sectors exhibiting greater sensitivity to transport-mode cost shocks. We embed these estimates in a multi-country, multi-sector general-equilibrium trade model with endogenous mode choice and input–output linkages. Counterfactual simulations of global changes in air-transport costs show that imposing a uniform transport-mode elasticity substantially misstates both the magnitude and cross-country dispersion of trade responses, underscoring the quantitative importance of sectoral heterogeneity in transport-mode adjustment.

Keywords: *Transport Mode Elasticities, Sectoral Heterogeneity, International Trade, Trade Costs*

JEL-codes: F10, F14, R40

We thank the editor, Gianmarco Ottaviano, and two anonymous referees for useful comments and suggestions.

*University of Colorado Boulder. Address: Department of Economics, 256 UCB, Boulder, CO 80309-0256; E-mail: jeong.ko@colorado.edu.

[†]University of Colorado Boulder and CESifo. Address: Department of Economics, 256 UCB, Boulder, CO 80309-0256; E-mail: sergey.nigai@colorado.edu.

[‡]University of Colorado Boulder. Address: Department of Economics, 256 UCB, Boulder, CO 80309-0256; E-mail: alec.truax@colorado.edu.

1 Introduction

The sorting of different goods across maritime, air, and land transportation is a fundamental feature of international trade, reflecting systematic differences among modes in terms of cost, speed, and reliability. Sector-specific elasticities of trade with respect to transport-mode costs are crucial for evaluating the effects of supply-chain disruptions and understanding the broader impacts of trade on multiple economic outcomes. Yet, empirical estimates of these sectoral transport-mode elasticities remain relatively scarce.

In this paper, we develop an estimation strategy for identifying sectoral transport-mode elasticities that can be applied to a wide range of sectoral classifications. The approach relies on an instrumental variables framework to estimate sector-level elasticities with respect to mode-specific transportation costs. We implement the method using data disaggregated by transport mode and sector, recovering elasticities for 21 broad manufacturing sectors. The estimates reveal substantial heterogeneity: sectors with high value-to-weight ratios are considerably more responsive to changes in transport costs, while bulk and heavy goods sectors display much lower sensitivity. This pattern suggests that the scope for reallocating trade shipments across transport modes differs systematically across sectors, making some sectors more sensitive than others to shocks affecting a particular transport mode.

To quantify the implications of our elasticity estimates, we embed them into a multi-country, multi-sector general equilibrium trade model with endogenous mode choice and input–output linkages. We use this framework to evaluate how a counterfactual increase in air-transportation costs would affect global trade patterns. The analysis shows that accounting for sectoral heterogeneity in transport-mode responses meaningfully alters both the magnitude and dispersion of predicted effects relative to models that impose uniform elasticities. To put these results into context, we compare the role of this heterogeneity to that of sectoral heterogeneity in the trade elasticity, another key parameter governing responses to trade-cost shocks, and find that the two are of a comparable order of magnitude. These results confirm that sectoral heterogeneity in transport-mode elasticities is quantitatively important for evaluating how transportation-cost shocks affect international trade and, ultimately, welfare.

This paper relates to three strands of literature. First, we connect to the extensive literature examining how bilateral barriers and transportation costs shape international trade and welfare (see [Anderson and van Wincoop, 2004](#); [Arkolakis et al., 2012](#); [Costinot and Rodriguez-Clare, 2014](#)). Additionally, our study aligns broadly with research investigating the effects of geography and infrastructure on transportation costs and trade (e.g., [Limão and Venables, 2001](#); [Hummels, 2007](#); [Volpe Martincus and Blyde, 2013](#); [Allen and Arkolakis, 2014, 2022](#); [Jaworski et al., 2023](#); [Fuchs and Wong, 2024](#)). Our contribution is to provide the sector-mode elasticities needed for measuring aggregate transport costs and evaluating their consequences for trade flows and welfare.

Second, several studies examine the impacts and elasticities associated with specific transportation modes. [Hummels and Schaur \(2013\)](#) and [Feyrer \(2019\)](#) compare air and sea freight; [Micco and Serebrisky \(2006\)](#), [Harrigan \(2010\)](#), [Söderlund \(2023\)](#), and [Besedeš et al. \(2024\)](#) focus on air transport; [Cosar and Demir \(2018\)](#) and [Jaworski and Kitchens \(2019\)](#) study road transport. An extensive literature further explores maritime transport costs and technology (see, among others, [Bernhofen et al., 2016](#); [Cosar and Demir, 2018](#); [Brancaccio et al., 2020](#); [Wong, 2022](#); [Ganapati et al., 2024](#)). Our work builds on these papers by estimating transport mode elasticities comprehensively across multiple sectors.

Finally, this paper is closely related to studies estimating aggregate transport-mode elasticities (e.g., [Lux, 2011](#); [Fuchs and Wong, 2024](#); [Tolva, 2024](#)), though those analyses differ in data coverage, empirical design, and identification strategy. Existing aggregate estimates typically range from 0.6 to 1.8, whereas our pooled specification yields an aggregate elasticity between 0.9 and 3.3. More importantly, our results reveal pronounced sectoral heterogeneity, underscoring the need to account for sector-specific variation in transport-mode elasticities.

2 Data Description

This paper draws on several data sources for descriptive statistics in this section, the empirical analysis in Section 3, and for calibrating the quantitative trade model with endogenous transport-mode choice in Section 5.1. To estimate sectoral transport-mode elasticities, we use monthly bilateral trade data from UN Comtrade ([COMTRADE, 2025](#)), disaggregated by transport mode and six-digit Harmonized System (HS6) product codes. These data report trade values on both *free on board* (FOB) and *cost, insurance, and freight* (CIF) bases, allowing us to construct ad valorem transport-cost measures. We supplement these data with great-circle distances from CEPII ([Mayer and Zignago, 2011](#)) and maritime distances from CERDI ([Bertoli et al., 2016](#)). We estimate elasticities for broad sectors based on the sectoral classification of the Global Trade Analysis Project (GTAP) version 11 ([Aguiar et al., 2023](#)), aligning the empirical analysis with the quantitative model. We report sectoral and country coverage in the Appendix.

For the quantitative model in Section 5.1, we combine the estimated elasticities with GTAP data on production, consumption, input-output linkages, and bilateral sectoral trade, supplemented with transport-mode information from the UNCTAD Global Transport Costs Dataset ([Hoffmeister et al., 2022](#)). We restrict the sample to countries with sufficient coverage across the required datasets and usable calibration inputs. The resulting calibration data cover 126 countries and 65 sectors for the benchmark year 2017 listed in the Appendix.

2.1 Sectoral Patterns of Trade by Transport Mode

We document substantial sectoral heterogeneity in transport-mode dependence, motivating the estimation of sector-specific transport-mode elasticities. Using FOB trade values from UN Comtrade,

we calculate sectoral trade shares for air, sea, road, and rail, alongside a residual category covering other observed modes.¹ While our framework can accommodate additional modes, limited disaggregated trade data constrain their separate treatment, particularly for less common modes such as pipelines.

Table 1: Sectoral Trade Shares by Transport Mode

GTAP Sector	Description	Air (%)	Sea (%)	Road (%)	Rail (%)	Other (%)
AFP	Agriculture and food processing	1.48	59.65	36.26	0.50	2.11
BPH	Basic pharmaceutical products	26.56	9.38	59.74	0.00	4.32
CHM	Chemical products	2.62	57.10	35.79	0.56	3.92
EEQ	Electrical equipment	6.73	22.41	64.40	1.33	5.13
ELE	Computer, electronic and optical prod.	34.42	14.98	44.92	0.43	5.24
ENG	Energy	0.16	81.90	7.80	1.77	8.37
FMP	Metal products	4.82	23.62	63.99	0.82	6.74
LS	Ferrous metals	0.19	64.76	31.43	1.94	1.67
LEA	Leather products	9.34	31.96	48.16	0.33	10.20
MVH	Motor vehicles and parts	0.65	33.13	55.86	5.18	5.18
NFM	Metals n.e.c.	43.39	25.86	29.54	0.03	1.18
NMM	Mineral products n.e.c.	2.30	38.11	53.70	0.53	5.37
OFD	Food products n.e.c.	0.84	36.17	57.60	0.18	5.22
OME	Machinery and equipment n.e.c.	5.98	35.12	52.04	0.49	6.37
OMF	Manufactures n.e.c.	10.01	9.56	30.30	0.24	49.90
OTH	Goods n.e.c.	0.98	43.36	45.27	0.13	10.27
OTN	Transport equipment n.e.c.	21.04	25.58	49.99	0.29	3.10
PPP	Paper products, printing	1.66	48.34	44.75	0.30	4.94
RPP	Rubber and plastic products	2.65	27.09	62.52	0.61	7.14
TEX	Textiles	2.57	52.82	40.57	0.18	3.85
WAP	Wearing apparel	6.17	19.80	69.63	0.14	4.27
Average		8.79	36.22	46.87	0.76	7.36
Std. dev.		12.16	18.97	14.89	1.14	10.04

Notes: Shares are calculated from FOB trade values using 15,840,328 monthly bilateral observations covering 153 countries and 21 GTAP-based sectors during 2016–2025. For estimation purposes, the sample retains country-pair-product-transport-mode combinations observed in at least 90 of the 120 months. The final two rows report the mean and standard deviation across sectors. *Source:* UN Comtrade.

We report computed transport-mode shares for each of the 21 aggregate sectors in Table 1. The results reveal pronounced heterogeneity in modal usage across sectors. For instance, 64.8% of trade in ferrous metals is transported by sea and another 31.4% by road, with only 0.2% shipped by air. In contrast, among basic pharmaceuticals, 26.6% of trade moves by air and 59.7% by road, while just 9.4% relies on sea transport.

Variation in modal shares reflects key differences in sectoral characteristics, particularly value-to-weight ratios and time sensitivity (Hummels, 2007; Harrigan, 2010). Sectors producing lighter, high-value goods where speed substantially lowers trade costs (e.g., pharmaceuticals) favor air transport whereas sectors with heavier or bulkier products (e.g., ferrous metals) rely on maritime

¹The “other” category includes inland waterways, pipelines, cables, postal consignments, courier shipments, and self-propelled goods as well as multi-mode adjustment. Data limitations preclude an analysis of multimodal transportation; see Fuchs and Wong (2024) for an approach incorporating multimodal transport networks. In some cases, UN Comtrade reports positive road or rail flows for country pairs without a feasible overland connection. We use the modal shares as reported in the data, but our results are robust to setting the overland share to zero for such pairs.

shipping to cover longer distances at lower per-unit costs. This heterogeneity suggests that incorporating sector-specific transport mode choices and elasticities is crucial for calculating the responsiveness of international trade flows to different transport cost shocks.

3 Estimation

In this section, we propose a framework for estimating sectoral transport-mode elasticities based on a general discrete-choice model with multiple alternatives. Estimating these elasticities poses two major empirical challenges. First, conventional gravity-based identification strategies, developed to estimate aggregate trade elasticities (e.g., [Caliendo and Parro, 2014](#); [Fontagné et al., 2022](#)), typically exploit tariff variation across sectors. Because tariffs do not vary at the transport-mode level, these methods cannot be directly applied. Second, transportation modes are endogenously chosen by exporters and importers, so estimation requires valid instruments at the sector-mode level.

Our estimation framework overcomes these challenges by (i) explicitly incorporating measured sector- and transport-mode-specific costs and (ii) constructing plausibly exogenous instrumental variables based on global transportation shocks, while remaining consistent with a broad class of structural models of international trade that yield a log-linear gravity equation for trade flows.

3.1 Estimating Framework

Our empirical strategy accommodates any sectoral classification with suitable data. We estimate transport-mode elasticities for 21 broad sectors aggregated from the GTAP classification used in the quantitative exercise in Section 5. Observations are indexed by (m, ij, h, s, t) , where m denotes transport mode, ij an exporter-importer pair, h an HS6 product nested within broad sector s ($h \in s$), and t the time period. The sample covers 2016–2025. Our baseline specification uses monthly observations but we also report quarterly and annual estimates.

The share of goods shipped by mode m from exporter i to importer j in sector (h, s) at time t is modeled as:

$$\pi_{ij,t}^m(h, s) = \frac{\left[\kappa_{i,t}^m(s) \chi_{ij,t}(h, s) \zeta_{ij}^m(s) \varphi_{j,t}^m(s) \right] \tau_{ij,t}^m(h, s)^{-\rho(s)}}{\sum_{m'} \left[\kappa_{i,t}^{m'}(s) \chi_{ij,t}(h, s) \zeta_{ij}^{m'}(s) \varphi_{j,t}^{m'}(s) \right] \tau_{ij,t}^{m'}(h, s)^{-\rho(s)}}, \quad (1)$$

where $\tau_{ij,t}^m(h, s)$ represents ad valorem transport-mode-sector-specific costs. The other terms reflect economic factors that shape the attractiveness of each transportation mode:

- $\kappa_{i,t}^m(s)$: exporter-time-mode-sector factors, e.g., upgrades of air-cargo facilities or maritime ports in exporting countries.
- $\chi_{ij,t}(h, s)$: exporter-importer-time-subsector factors, e.g., subsector-specific bilateral tariff changes

or regulatory standards.

- $\zeta_{ij}^m(s)$: exporter-importer-mode-sector fixed factors, e.g., existence of direct maritime routes or absence of land-based infrastructure.
- $\varphi_{j,t}^m(s)$: importer-time-mode-sector factors, e.g., infrastructure investments in destination airports or port facilities.

Under the functional-form assumption from equation (1), the estimating equation for bilateral sector-specific transport-mode shares takes a log-additive form:

$$\log \pi_{ij,t}^m(h, s) = \delta_{ij,t}(h, s) + \delta_{i,t}^m(s) + \delta_{j,t}^m(s) + \delta_{ij}^m(s) - \rho(s) \log \tau_{ij,t}^m(h, s) + \epsilon_{ij,t}^m(h, s), \quad (2)$$

where the δ terms represent fixed effects, and $\epsilon_{ij,t}^m(h, s)$ is a stochastic error term. Our identification relies on both sectoral and subsectoral variation in transport-mode usage across country pairs. We thus assume that transport-mode elasticities $\rho(s)$ are constant across subsectors $h \in s$.

Estimating equation (2) requires: (i) observed bilateral mode shares at the subsector level, $\pi_{ij,t}^m(h, s)$; (ii) an appropriate set of fixed effects δ 's; and (iii) measures of mode-sector-specific transport costs, $\tau_{ij,t}^m(h, s)$. While (i) can be directly calculated from the data and (ii) involves standard econometric controls, direct measurement of (iii) is empirically challenging.

In our data set, bilateral trade flows by transport mode are recorded in two valuation measures: cost-insurance-freight $\text{CIF}_{ij,t}^m(h, s)$ and free-on-board $\text{FOB}_{ij,t}^m(h, s)$. We calculate mode shares as:

$$\pi_{ij,t}^m(h, s) = \frac{\text{CIF}_{ij,t}^m(h, s)}{\sum_{m'} \text{CIF}_{ij,t}^{m'}(h, s)}.$$

Given the availability of CIF and FOB values, we measure *iceberg* mode-specific transport costs as follows:

$$\tau_{ij,t}^m(h, s) = \frac{\text{CIF}_{ij,t}^m(h, s)}{\text{FOB}_{ij,t}^m(h, s)}.$$

While intuitive, our measure of $\tau_{ij,t}^m(h, s)$ captures not only pure transportation costs but also non-freight charges, such as insurance, embedded in the CIF-FOB margin. This distinction matters for the interpretation of iceberg trade costs, e.g., whether they represent freight alone or a broader measure of trade costs, but is consistent with our estimation strategy for two reasons.

First, a broader measure of mode-specific trade costs may better capture the costs relevant for substitution across transport modes. Firms may choose between modes based on generalized shipping costs rather than freight charges alone, so differences in insurance costs across modes are themselves part of the mode-choice decision. Under this interpretation, the CIF-FOB ratio is an

appropriate measure for estimating sectoral transport-mode elasticities and should be viewed as a broad measure of mode-specific trade costs that includes both transportation and insurance.

Second, even if the objective is to isolate differences in pure transportation costs across modes, the fixed-effect structure in equation (2) would be appropriate as it absorbs much of the relevant variation in non-transportation costs, including arbitrary product-level heterogeneity that is common across transport modes. To see this, decompose $\ln \tau_{ij,t}^m(h, s)$ as:

$$\ln \tau_{ij,t}^m(h, s) = \ln \phi_{ij,t}^m(h, s) + \bar{l}_{ij,t}(h, s) + \Delta l_{ij,t}^m(h, s), \quad (3)$$

where $\phi_{ij,t}^m(h, s)$ denotes the pure transportation component, $\bar{l}_{ij,t}(h, s)$ reflects insurance and other non-transportation costs that are common across transport modes, and $\Delta l_{ij,t}^m(h, s)$ denotes the corresponding mode-specific deviation. This decomposition allows us to clarify the identifying restriction required to estimate sectoral transport-mode elasticities. Our framework allows product characteristics such as fragility and perishability to affect insurance costs heterogeneously across subsectors h , provided that this heterogeneity is common across transport modes. Such variation is absorbed by the $\bar{l}_{ij,t}(h, s)$ fixed effects. The identifying restriction constrains only the residual mode-specific component $\Delta l_{ij,t}^m(h, s)$, which may vary across transport modes, country pairs, sectors, and time, but is required to be common across subsectors h within a sector s .

Economically, this restriction allows subsector characteristics to determine the baseline level of insurance costs, while treating the additional premium associated with the transport mode as a broader sector-level feature. For example, perishability or fragility may make one product substantially more expensive to insure than another under either mode, while the additional insurance cost of sea relative to air may reflect differences in exposure to route-specific risks that are shared across products within the same broad sector. The assumption therefore permits substantial within-sector heterogeneity in insurance costs and only restricts only how that heterogeneity interacts with the choice of transport mode.

This interpretation is also consistent with standard features of cargo insurance used in international trade. For example, under the International Chamber of Commerce's Uniform Customs and Practice for Documentary Credits, when a letter of credit requires insurance but does not specify the amount of coverage, minimum coverage is set at 110% of the value of the goods. This common valuation rule applies independently of the particular transport mode and is therefore consistent with our restriction. Formally, we impose the following assumption:

Assumption 1. *The non-transportation component of the CIF–FOB ratio can be decomposed as:*

$$l_{ij,t}^m(h, s) = \bar{l}_{ij,t}(h, s) + \Delta l_{ij,t}^m(s),$$

where the mode-invariant component $\bar{l}_{ij,t}(h, s)$ varies at the $\{ij \times h \times s \times t\}$ level, while the mode-specific component $\Delta l_{ij,t}^m(s)$ varies at the $\{ij \times m \times s \times t\}$ level.

Table 2: Estimates of Transport Mode Elasticities by GTAP Sector

Sector	Month				Quarter				Annual			
	OLS		IV		OLS		IV		OLS		IV	
	Coef.	Obs.	Coef.	Obs. [F-stat]	Coef.	Obs.	Coef.	Obs. [F-stat]	Coef.	Obs.	Coef.	Obs. [F-stat]
Pooled	-0.933 (.178)	6562016 .	-3.298 (.752)	6562016 [19097]	-1.16 (.23)	2354529 .	-3.093 (.677)	2339416 [35674]	-1.501 (.307)	596609 .	-2.872 (.592)	592820 [22677]
AFP	-2.769 (1.57)	36131 .	-9.647 (2.347)	31775 [1014]	-3.913 (2.254)	13022 .	-9.774 (2.276)	11550 [1503]	-5.141 (2.925)	3289 .	-9.712 (2.968)	2921 [2231]
BPH	-2.467 (.695)	58744 .	-11.661 (2.147)	58184 [3045]	-3.283 (.913)	21586 .	-9.55 (2.35)	21394 [9196]	-4.165 (1.261)	5460 .	-7.271 (2.298)	5412 [79613]
CHM	-1.172 (.172)	473142 .	-4.459 (.759)	467666 [6848]	-1.608 (.26)	171615 .	-4.421 (.753)	169761 [8258]	-2.238 (.426)	43408 .	-4.123 (.724)	42944 [3118]
EEQ	-1.147 (.321)	819819 .	-3.639 (1.383)	815689 [5508]	-1.394 (.425)	289775 .	-3.492 (1.332)	288367 [9806]	-1.726 (.584)	73331 .	-3.347 (1.294)	72979 [10998]
ELE	-.981 (.605)	707985 .	-1.563 (1.402)	706273 [3603]	-.958 (.669)	251948 .	-1.489 (1.31)	251372 [9441]	-.99 (.777)	63883 .	-1.444 (1.239)	63737 [5163]
ENG	-.149 (.262)	9399 .	-.828 (1.139)	9010 [28]	.253 (.325)	3412 .	-2.539 (2.04)	3280 [52]	.61 (.745)	861 .	-3.852 (2.166)	829 [81]
FMP	-.96 (.179)	651242 .	-4.512 (.979)	647274 [13593]	-1.183 (.979)	231806 .	-3.892 (.896)	230462 [17175]	-1.679 (.326)	58766 .	-3.468 (.719)	58430 [22583]
LS	-1.038 (.256)	83678 .	-5.852 (1.039)	83317 [1773]	-1.472 (.314)	30531 .	-4.903 (.954)	30403 [2437]	-2.215 (.471)	7713 .	-3.926 (.947)	7681 [8478]
LEA	-1.472 (.493)	128987 .	-5.068 (1.834)	128607 [537]	-1.933 (.65)	45481 .	-4.921 (1.666)	45353 [3117]	-2.623 (.913)	11546 .	-5.098 (1.556)	11514 [702]
MVH	-.035 (.067)	356588 .	-.683 (.292)	355092 [8129]	-.088 (.092)	124630 .	-.645 (.284)	124113 [20114]	-.19 (.128)	31587 .	-.711 (.283)	31450 [175158]
NFM	-2.327 (.194)	42175 .	-8.004 (1.294)	42175 [48536]	-3.495 (.447)	15407 .	-7.405 (1.334)	15407 [55237]	-4.343 (.661)	3892 .	-6.633 (1.216)	3892 [121255]
NMM	-.863 (.152)	154917 .	-2.904 (.568)	153786 [12285]	-1.167 (.224)	55985 .	-2.828 (.591)	55603 [14978]	-1.566 (.317)	14194 .	-2.625 (.545)	14098 [25651]
OFD	-2.805 (.517)	46901 .	-11.834 (2.489)	43679 [323]	-3.28 (.903)	17206 .	-12.138 (3.435)	16120 [747]	-4.322 (1.409)	4353 .	-9.17 (3.446)	4081 [141]
OME	-.98 (.33)	1220573 .	-4.127 (1.09)	1218715 [45742]	-1.247 (.401)	433079 .	-3.78 (1.008)	432439 [33893]	-1.596 (.481)	109653 .	-3.372 (.875)	109493 [69115]
OMF	-2.129 (.286)	310112 .	-9.688 (1.523)	306334 [4155]	-3.048 (.468)	110442 .	-8.673 (1.85)	109162 [12315]	-4.16 (.761)	27973 .	-7.933 (1.804)	27653 [26945]
OTH	-.425 (.369)	21798 .	-5.399 (1.504)	20864 [201]	-.54 (.56)	8003 .	-3.873 (2.013)	7683 [1153]	-1.018 (.97)	2052 .	-3.815 (2.04)	1972 [2283]
OTN	-1.892 (.361)	41663 .	-7.859 (1.658)	41195 [19809]	-2.324 (.529)	15024 .	-7.014 (1.716)	14888 [41807]	-3.496 (.988)	3805 .	-7.074 (1.643)	3771 [43827]
PPP	-.68 (.155)	128154 .	-1.967 (.983)	124566 [2963]	-.675 (.251)	46677 .	-1.661 (.932)	45461 [3842]	-.724 (.341)	11851 .	-1.419 (.862)	11547 [4453]
RPP	-.577 (.146)	553045 .	-2.271 (.732)	549053 [8837]	-.761 (.198)	196082 .	-2.034 (.657)	194738 [18293]	-1.059 (.278)	49720 .	-1.851 (.565)	49384 [10506]
TEX	-1.401 (.213)	191378 .	-5.732 (.848)	190612 [88424]	-1.922 (.258)	70134 .	-5.507 (.79)	69878 [468374]	-2.654 (.363)	17826 .	-5.151 (.69)	17762 [226552]
WAP	-1.234 (.388)	570204 .	-5.837 (1.897)	568150 [225]	-1.404 (.442)	202684 .	-5.476 (1.695)	201982 [225]	-1.637 (.719)	51446 .	-4.416 (1.575)	51270 [80]

Notes: The table reports pooled and sector-specific OLS and IV estimates using monthly, quarterly, and annual data. Standard errors clustered by country pair appear in parentheses; first-stage Kleibergen–Paap F-statistics appear in brackets. All specifications include fixed effects defined in equation (2).

We first estimate equation (2) by OLS and report the results in Table 2. In the baseline monthly specification, the pooled elasticity is -0.93 . Sectoral estimates average -1.31 and range from -2.81 to -0.04 . Estimates for energy and for motor vehicles and parts are closest to zero and statistically indistinguishable from it. Food products n.e.c., agriculture and food processing, and basic pharmaceuticals exhibit the largest magnitudes.

The broad sectoral patterns persist in quarterly and annual specifications, constructed from within-period monthly averages rather than sums to limit aggregation effects. The pooled OLS elasticity

increases in absolute value from 0.93 monthly to 1.16 quarterly and 1.50 annually, with most sectors following a similar pattern. This persistence across frequencies is reassuring, while the larger annual magnitudes are consistent with firms having more time to adjust their transport-mode choices.

3.2 Instrumental Variable Approach

Although the heterogeneity in the OLS estimates of ρ across sectors underscores the importance of adopting a sector-specific approach, these estimates may be biased due to measurement error and reverse causality. In particular, the CIF-FOB ratio may be measured with error, and the measured mode-specific transportation costs, $\tau_{ij,t}^m(h, s)$, may be correlated with unobserved determinants of transport mode choice. For example, stronger demand for a particular mode may simultaneously raise its trade share and transportation cost. To address these concerns, we construct an instrument that exploits global mode-specific transportation shocks and their differential effects across country pairs through exogenous bilateral geography. The approach is related to [Feyrer \(2019\)](#) and [Nigai \(2023\)](#).

We characterize bilateral geography using two exogenous measures: log great-circle distance, $\ln cirdist_{ij}$, and log sea distance, $\ln seadist_{ij}$. The identifying variation in our IV approach arises from the interaction of these geographic characteristics with time-varying global transportation conditions. To fix ideas, consider two country pairs at similar great-circle distance, one connected by a relatively direct maritime route and the other requiring a substantially longer sea route because of geographic detours or maritime chokepoints. An increase in bunker fuel prices raises sea transportation costs more for the latter pair, while air costs, which scale with great-circle distance, rise similarly for both. More generally, because sea and great-circle distances diverge across country pairs, global mode-specific transportation shocks shift relative transport costs differently across routes. This is the variation exploited by our instrument.

We estimate global time-varying changes in transportation conditions for each sector-mode combination (s, m) using the gravity equation approach from [Feyrer \(2019\)](#):

$$\ln \tau_{ij,t}^m(h, s) = \mu_{i,t}^m(s) + \mu_{j,t}^m(s) + \mu_{ij}^m(h, s) + \sum_{\ell \in T} \hat{\xi}_{\ell}^{cir,m}(s) \mathbf{1}_{t=\ell} \ln cirdist_{ij} + \sum_{\ell \in T} \hat{\xi}_{\ell}^{sea,m}(s) \mathbf{1}_{t=\ell} \ln seadist_{ij} + e_{ij,t}^m(h, s). \quad (4)$$

The fixed effects $\mu_{i,t}^m(s)$ and $\mu_{j,t}^m(s)$ absorb exporter- and importer-mode-sector-time shocks, while $\mu_{ij}^m(h, s)$ captures time-invariant bilateral mode-sector characteristics. The estimated coefficients, $\hat{\xi}_{\ell}^{cir,m}(s)$ and $\hat{\xi}_{\ell}^{sea,m}(s)$, measure global mode-sector-time-specific shocks. Using these estimates, we construct instruments:

$$z_{ij,t}^m(h, s) = \hat{\mu}_{ij}^m(h, s) + \sum_{\ell \in T} \hat{\xi}_{\ell}^{cir,m}(s) \mathbf{1}_{t=\ell} \ln cirdist_{ij} + \sum_{\ell \in T} \hat{\xi}_{\ell}^{sea,m}(s) \mathbf{1}_{t=\ell} \ln seadist_{ij}. \quad (5)$$

Thus, time variation in $z_{ij,t}^m(s)$ is generated exclusively by the interaction between changes over time

in global mode-specific transportation conditions and predetermined bilateral geography. The validity of the instrument requires that, conditional on the fixed effects included in equation (2), this predicted variation affects transport-mode shares only through its effect on mode-specific transportation costs. Formally, IV identification of the transport-mode elasticities relies on the following exclusion restriction:

Assumption 2. *Conditional on the fixed effects in equation (2), variation generated by interactions between global mode-sector-specific transportation conditions and predetermined bilateral geography affects transport-mode shares $\ln \pi_{ij,t}^m(h, s)$ only through its effect on mode-specific transportation costs $\ln \tau_{ij,t}^m(h, s)$.*

We argue that this exclusion restriction is plausible because the identifying variation comes from differential exposure of country pairs to common transportation shocks through predetermined geography. A violation would therefore require global shocks to alter relative mode use across routes in a way that is systematically related to geography but operates through a channel other than transportation costs. While we cannot rule out such a channel entirely, it would have to be simultaneously global, geography-dependent, mode-specific, and unrelated to transportation costs. In this sense, Assumption 2 rules out only unobserved shocks with this particular joint structure.

We estimate equation (2) by IV and report the results in Table 2.² The first-stage F -statistics indicate that the instruments $z_{ij,t}^m(h, s)$ are strongly correlated with measured transportation costs. The IV estimates are systematically larger in magnitude than their OLS counterparts. In the monthly pooled specification, the estimate changes from -0.93 under OLS to -3.30 under IV, with larger IV magnitudes in every sector.

This difference is consistent with attenuation from classical measurement error in (log) CIF-to-FOB ratios and with endogeneity in transportation costs. For example, a surge in demand for air shipping could raise its trade share while pushing up freight rates when capacity is limited. Higher prices would then coincide with greater use of air transport, obscuring the negative effect of costs on mode choice and making OLS estimates biased toward zero. This is one possible mechanism; other unobserved factors that increase both prices and mode shares could generate bias in the same direction.

To explore sectoral drivers of transport-mode elasticities, we first construct a sector level measure of value per weight:

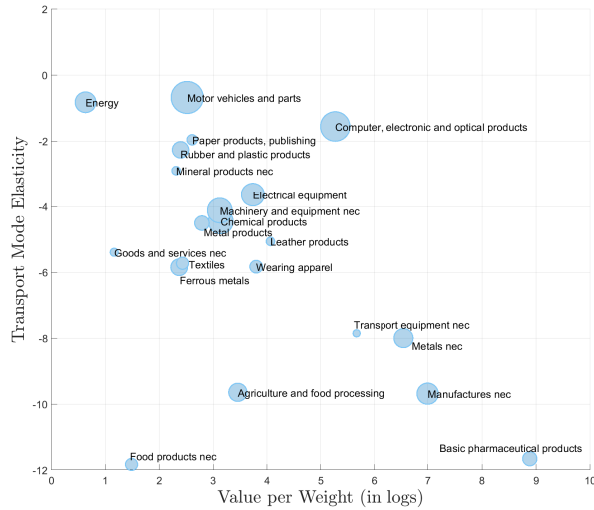
$$VPW(s) = \frac{\sum_{m,ij,h,t} \text{FOB}_{ij,t}^m(h, s)}{\sum_{m,ij,h,t} \text{Net Weight}_{ij,t}^m(h, s)}.$$

We then plot the estimated IV elasticities against $VPW(s)$ in Panel A of Figure 1, which reveals

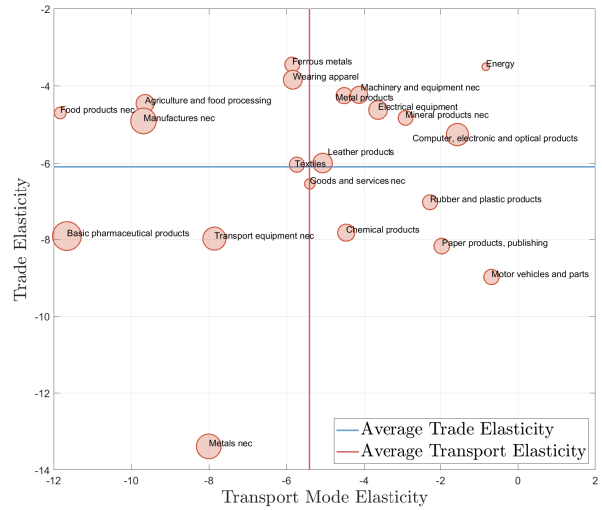
²The reported results use the 2SLS estimator. As documented by Mikusheva and Sun (2024), the bias of this estimator increases with the number of instruments, proportional to sample size. To test the robustness of our estimates, we performed quarterly, sector-level regressions using the JIVE estimator as recommended by that paper. Across all sectors, the difference between 2SLS and JIVE estimates was negligible and did not affect our results.

a clear negative relationship. Intuitively, because transport costs take a large share of total value in low value-per-weight sectors (e.g., paper products), these sectors are primarily reliant on the cheapest bulk shipping modes, which severely restricts viable alternatives and results in relatively inelastic transport-mode choice.

Panel A: Transport-mode Elasticities and Value per Weight



Panel B: Transport-mode Elasticities and Trade Elasticities



Notes: These figures illustrate the relationship between transport mode elasticities and key sectoral traits. Panel A plots IV estimates of transport mode elasticities, $\rho(s)$, against the logarithm of $VPW(s)$, measured in dollars per kilogram. Panel B categorizes sectors by their transport mode elasticities and trade elasticities (from Fontagné et al. (2022)), each expressed relative to their average values. In both panels, marker size is scaled by the total nominal FOB value of international trade from 2016 to 2025.

Figure 1: SECTORAL CHARACTERISTICS AND TRANSPORT MODE ELASTICITIES

While our estimates of $\rho(s)$ capture how firms substitute between transport modes, the ultimate effect on total trade flows is also mediated by the standard trade elasticity of substitution between goods, which we denote as $\theta(s)$. As we derive in Section 4, the theory-consistent elasticity of international trade with respect to a change in a single mode's cost is a function of both parameters, equal to $-\frac{\theta(s)}{\rho(s)}$. Since the focus of this paper is on the transport-mode elasticity $\rho(s)$, we borrow established estimates of sectoral trade elasticities, $\theta(s)$, from Fontagné et al. (2022), who provide them at our required level of aggregation.³

Panel B of Figure 1 examines the relationship between our estimated IV sectoral transport-mode elasticities and the corresponding trade elasticity. The figure is divided into four quadrants determined by the average value of each elasticity, offering a typology of sectors according to their sensitivity to transport-specific and general trade cost shocks. The two elasticities exhibit little linear association across sectors. For example, motor vehicles and parts have a small transport-mode

³Fontagné et al. (2022) provide trade elasticities at GTAP vers. 11 aggregation at <https://sites.google.com/view/product-level-trade-elasticity>. We follow the same aggregation for $\rho(s)$, taking a simple average across more disaggregated categories in AFP, ENG, and OTH.

elasticity but a large trade elasticity in absolute value (0.7 versus 9); food products n.e.c. display the opposite pattern (11.8 versus 4.7). These differences highlight the distinct adjustment margins captured by the two parameters, which we jointly incorporate into the quantitative model in the next section.

4 Model

To assess the implications of our elasticity estimates, $\rho(s)$, we embed them in a general equilibrium trade model. In this section, we present an Armington model of international trade with endogenous transport-mode choices and sectoral input-output linkages, building on the frameworks of [Allen and Arkolakis \(2014\)](#) and [Jaworski et al. \(2023\)](#). The model also shares key features with other trade frameworks in which transportation modes are chosen through a discrete-choice mechanism.

There are J countries in the world populated by L_j workers across S sectors. Workers are mobile across sectors but not across countries. Production in each sector uses labor and intermediate inputs. Consumers in country j have an upper-tier Cobb-Douglas utility function with weights $\alpha_j(s)$ that sum to unity across sectors. The associated indirect utility function is:

$$W_j = \frac{I_j}{P_j}, \text{ where } P_j = \prod_{s \in S} \left(\frac{P_j(s)}{\alpha_j(s)} \right)^{\alpha_j(s)}, \quad (6)$$

where I_j is total nominal consumer income which includes labor income, $V_j = L_j w_j$, and a lump-sum transfer, T_j .

Within each sector s , countries produce distinct varieties, $q_i(s)$, which are aggregated prior to consumption by consumers and firms according to a constant elasticity of substitution (CES) function of the form:

$$Q_j(s) = \left(\sum_i q_i(s)^{\frac{\theta(s)}{\theta(s)+1}} \right)^{\frac{\theta(s)+1}{\theta(s)}}.$$

Producers in sector s and country i have a level of productivity, $A_i(s)$, and employ labor L_i at a wage w_i together with intermediate inputs $Q_i(s)$ at price $P_i(s)$ such that their marginal production cost is specified as:

$$M_i(s) = C_i(s) \frac{w_i^{\gamma_i(s)} P_i(s)^{1-\gamma_i(s)}}{A_i(s)}, \text{ where } \gamma_i(s) \in (0, 1), \quad (7)$$

where $C_i(s)$ is a constant and $\mathbb{P}_i(s)$ is a CES function that aggregates inputs as follows:

$$\mathbb{P}_i(s) = \prod_{\dot{s} \in \dot{S}} \left(\frac{P_i(\dot{s})}{\eta_i(\dot{s}s)} \right)^{\eta_i(\dot{s}s)}, \text{ where } \sum_{\dot{s} \in \dot{S}} \eta_i(\dot{s}s) = 1, \quad (8)$$

with $\dot{s}$ denoting the sector that supplies intermediate inputs to sector s and $\eta_i(\dot{s}s)$ the parameters that govern input-output linkages.

Following [Allen and Arkolakis \(2014\)](#), we assume every exporter country i and importer country j has a mass of identical traders who choose to transport goods via different modes $m \in \{1, \dots, M\}$. Each transport mode is characterized by its iceberg trade cost $\tau_{ij}^m(s) \geq 1$. Traders draw i.i.d. shocks from an extreme value distribution with scale parameter $\chi_{ij}^m(s)$ that captures non-transport determinants influencing how likely traders are to choose mode m , and shape parameter $\rho(s)$. We then specify the share of goods from sector s transported using mode m from i to j as:

$$\pi_{ij}^m(s) = \frac{\chi_{ij}^m(s) \tau_{ij}^m(s)^{-\rho(s)}}{\sum_{m'} \chi_{ij}^{m'}(s) \tau_{ij}^{m'}(s)^{-\rho(s)}}. \quad (9)$$

It is well known in the literature that trade costs include components unrelated to transport costs. Therefore, we assume that countries incur other trade costs when exporting goods from i to j , common to all modes m , that are captured by $t_{ij}(s)$. Then, the total trade costs between countries i and j can be specified as:

$$d_{ij}(s) = T(s) t_{ij}(s) \left(\sum_m \chi_{ij}^m(s) \tau_{ij}^m(s)^{-\rho(s)} \right)^{-\frac{1}{\rho(s)}}, \quad (10)$$

where $T(s)$ is a constant.

With this specification of trade costs, we can characterize bilateral trade shares:

$$\lambda_{ij}(s) = \left(C_i(s) \frac{w_i^{\gamma_i(s)} \mathbb{P}_i(s)^{1-\gamma_i(s)}}{A_i(s)} \right)^{-\theta(s)} P_j(s)^{\theta(s)} d_{ij}(s)^{-\theta(s)}, \quad (11)$$

defining the CES price index as:

$$P_j(s) = \left(\sum_k \left[C_k(s) \frac{w_k^{\gamma_k(s)} \mathbb{P}_k(s)^{1-\gamma_k(s)}}{A_k(s)} \right]^{-\theta(s)} d_{kj}(s)^{-\theta(s)} \right)^{-\frac{1}{\theta(s)}}. \quad (12)$$

Then, the nominal trade flow from i to j in sector s is specified as $X_{ij}(s) = \lambda_{ij}(s) Y_j(s)$, where $Y_j(s)$ is the total demand for goods from sector s in country j , consisting of final consumer and intermediate

firm demands:

$$Y_i(s) = \sum_s (1 - \gamma_i(s)) \eta_i(ss) \sum_j \lambda_{ij}(s) Y_j(s) + \alpha_i(s) I_i, \quad (13)$$

where $I_i = L_i w_i + D_i$ includes D_i as an exogenous deficit constant. We close the model by specifying the trade balance condition:

$$\sum_s \sum_j \lambda_{ji}(s) Y_i(s) - D_i = \sum_s \sum_j \lambda_{ij}(s) Y_j(s). \quad (14)$$

We define equilibrium as follows:

Definition 1. Given economic primitives related to consumer preferences $\{\alpha_i(s), \theta(s)\}$, production functions $\{\gamma_i(s), \eta_i(ss)\}$, transport mode choices $\{\chi_{ij}^m(s), \tau_{ij}^m(s)\}$, trade costs $\{t_{ij}(s)\}$, and deficit constants $\{D_i\}$, an equilibrium is a vector of wages, $\mathbf{w} \in \mathbb{R}_+$, and prices, $\mathbf{P} \in \mathbb{R}_+$, such that the conditions in (6), (7), (8), (9), (11), (12), (13), and (14) are satisfied for all m, s, i and j .

Following Dekle et al. (2007) and Caliendo and Parro (2014), we reformulate the model in terms of relative changes. Let a' denote the counterfactual value of variable a , with $\hat{a} = a'/a$. This reformulation allows us to solve for counterfactual equilibria under arbitrary shocks to $\tau_{ij}^m(s)$ using hat algebra. For example, to obtain the change in bilateral trade costs, we take the counterfactual-to-baseline ratio of equation (10), holding $T(s)$, $t_{ij}(s)$, and $\chi_{ij}^m(s)$ fixed. Using $\tau_{ij}^{m'}(s) = \hat{\tau}_{ij}^m(s) \tau_{ij}^m(s)$, this gives

$$\hat{d}_{ij}(s) = \left(\sum_m \pi_{ij}^m(s) \hat{\tau}_{ij}^m(s)^{-\rho(s)} \right)^{-\frac{1}{\rho(s)}},$$

where $\pi_{ij}^m(s)$ is the baseline transport-mode share.

Conditional on observing $\{\eta_i(ss), \pi_{ij}^m(s), \lambda_{ij}(s), V_i\}$, we solve the following system of equations:

- (i) Change in marginal cost: $\hat{M}_i(s) = \hat{w}_i^{\gamma_i(s)} \hat{P}_i(s)^{1-\gamma_i(s)}$
- (ii) Change in price of intermediates: $\hat{P}_i(s) = \prod_{s \in S} \hat{P}_i(s)^{\eta_i(ss)}$
- (iii) Change in trade costs: $\hat{d}_{ij}(s) = \left(\sum_m \pi_{ij}^m(s) \hat{\tau}_{ij}^m(s)^{-\rho(s)} \right)^{-\frac{1}{\rho(s)}}$
- (iv) Counterfactual trade shares: $\lambda'_{ij}(s) = \lambda_{ij}(s) \left[\hat{d}_{ij}(s) \hat{M}_i(s) / \hat{P}_j(s) \right]^{-\theta(s)}$
- (v) Change in CES prices: $\hat{P}_i(s) = \left(\sum_k \lambda_{ki}(s) \left[\hat{d}_{ki}(s) \hat{M}_k(s) \right]^{-\theta(s)} \right)^{-\frac{1}{\theta(s)}}$
- (vi) Counterfactual absorption: $Y'_i(s) = \sum_s (1 - \gamma_i(s)) \eta_i(ss) \sum_j \lambda'_{ij}(s) Y'_j(s) + \alpha_i(s) (\hat{w}_i V_i + D_i)$
- (vii) Change in wages: $\sum_s \sum_j \lambda'_{ji}(s) Y'_i(s) - D_i = \sum_s \sum_j \lambda'_{ij}(s) Y'_j(s)$

5 Quantitative Analysis

This section describes our strategy for calibrating the model’s key structural parameters and presents a counterfactual simulation that illustrates the importance of allowing for heterogeneous transport-mode elasticities in trade analyses.

5.1 Calibration

We calibrate the model to the benchmark year 2017 using the GTAP and UNCTAD data introduced in Section 2. Using a trade-value-weighted concordance, we map products in the UNCTAD data to GTAP sectors and construct bilateral sector-specific transport-mode shares, which we use to allocate GTAP merchandise trade flows across transport modes. The sample covers 126 countries and 65 sectors (47 in manufacturing and 18 in services); it is smaller than the estimation sample because calibration requires coverage across all datasets used to discipline the model. Table A1 in the Appendix lists the countries and sectors included.

First, we calibrate the structural parameters $\{\theta(s), \alpha_i(s), \gamma_i(s), \eta_i(\dot{s}, s)\}$. For manufacturing sectors, we take the trade elasticities $\theta(s)$ from [Fontagné et al. \(2022\)](#). When a sector-specific estimate is unavailable, we assign the mean elasticity across sectors within the corresponding aggregate GTAP sector including services. We calculate the remaining parameters directly from GTAP data: (i) $\alpha_i(s)$ are the shares of income spent on goods from each sector s , calculated from observed consumption; (ii) $\gamma_i(s)$ are the ratios of value added to total output in each sector s ; and (iii) $\eta_i(\dot{s}, s)$ are the shares of total expenditure by each sector s devoted to intermediate inputs from sector $\dot{s}$.

Second, we calibrate $\{\lambda_{ij}(s), V_i, \pi_{ij}^m(s)\}$ to the 2017 benchmark equilibrium values: (i) $\lambda_{ij}(s)$ are calculated as the share of country j ’s expenditure on goods in sector s from country i constructed from GTAP trade and production data, (ii) V_i are calculated as total value added in country i across all sectors, (iii) $\pi_{ij}^m(s)$ are the shares of bilateral trade in sector s transported via mode m . Since we cannot observe $\pi_{ij}^m(s)$ for all country-pair-sector triads, we rely on imputations developed in [Hoffmeister et al. \(2022\)](#) to fill in missing values.⁴

5.2 Counterfactual Analysis

We use the calibrated model to quantitatively evaluate the importance of our central empirical finding – substantial sectoral heterogeneity in transport-mode elasticities. For this exercise, we simulate a uniform 13 percent counterfactual increase in air transport costs, such that $\hat{\tau}_{ij}^{air}(s) = 1.13$ for all sectors and country pairs. The magnitude of the counterfactual shock matches the magnitude of the cost decrease for air transport between 2012 and 2017, as measured by the price index of air freight services from the [U.S. Bureau of Labor Statistics \(2025a,b\)](#). We focus on air transport because it has experienced large and persistent cost declines in recent decades (see [Hummels, 2007](#);

⁴Transport-mode shares in [Hoffmeister et al. \(2022\)](#) are reported at HS6 level. We convert their figures to GTAP classification following [Aguilar \(2016\)](#).

Feyrer, 2019), which makes it a particularly instructive case. However, the results of this exercise are robust to alternative shocks that differ in magnitude or affect other transport modes.

Our analysis focuses on two outcomes of interest, welfare gains from trade and changes in bilateral trade shares, defined respectively as:

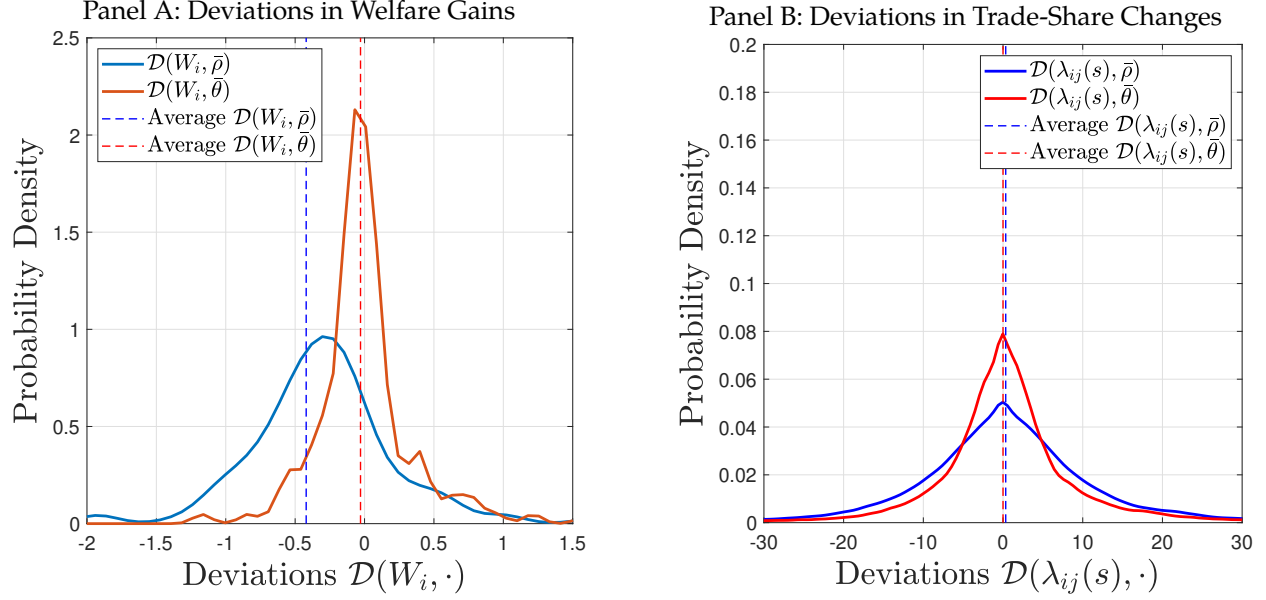
$$\Delta W_i = 100 \times (\hat{w}_i / \hat{P}_i - 1), \quad \Delta \lambda_{ij}(s) = 100 \times (\hat{\lambda}_{ij}(s) - 1).$$

We compute these changes under three elasticity scenarios: (i) the fully heterogeneous baseline, $\rho(s)$ and $\theta(s)$; (ii) homogeneous $\rho(s) = \bar{\rho}$, where $\bar{\rho} = 3.3$ from the pooled monthly IV specification, with heterogeneous $\theta(s)$; and (iii) heterogeneous $\rho(s)$ with homogeneous $\theta(s) = \bar{\theta}$, where $\bar{\theta} = 5.8$ denotes the average trade elasticity across sectors. The third case contextualizes the quantitative relevance of heterogeneous $\rho(s)$ against the well-studied heterogeneity in trade elasticities, $\theta(s)$ (see Caliendo and Parro, 2014; Costinot and Rodriguez-Clare, 2014). For each outcome variable $a \in \{W_i, \lambda_{ij}(s)\}$, we measure the consequence of imposing homogeneity in either transport-mode or trade elasticities with the following, corresponding deviations from the baseline:

$$\mathcal{D}(a, \bar{\rho}) = \Delta a(\bar{\rho}, \theta(s)) - \Delta a(\rho(s), \theta(s)), \quad \mathcal{D}(a, \bar{\theta}) = \Delta a(\rho(s), \bar{\theta}) - \Delta a(\rho(s), \theta(s)).$$

Panel A of Figure 2 plots the kernel densities of deviations in the welfare gains from trade under a counterfactual 13% increase in international air-transport costs, separately under homogeneous ρ and homogeneous θ . The average deviations are -0.42 and -0.03 percentage points, respectively. For our purposes, however, the mean is less informative because it largely captures a common level error that could, in principle, be reduced by recalibrating the homogeneous elasticity. More informative is the cross-country dispersion of the deviations, with standard deviations of 0.78 and 0.48, respectively. This dispersion captures how much the homogeneous specification misallocates the welfare effects of the shock across countries: even if the average effect were matched, it could still overstate gains for some countries and understate them for others. Because these differences reflect countries' sectoral composition and exposure to transport modes, they cannot be eliminated by choosing a different common elasticity. Both simplifying assumptions therefore meaningfully affect counterfactual welfare predictions, with the consequences of imposing a homogeneous ρ somewhat larger than, but broadly comparable to, those of imposing a homogeneous θ .

Panel B of Figure 2 plots the kernel densities of deviations in trade-share changes under the same counterfactual shock, $\mathcal{D}(\lambda_{ij}(s), \bar{\rho})$ and $\mathcal{D}(\lambda_{ij}(s), \bar{\theta})$. As in Panel A, our main interest is in the dispersion of these deviations. We report both unweighted standard deviations and standard deviations weighted by initial trade shares, so that very small trade flows do not disproportionately influence the comparison. The unweighted (weighted) standard deviations are 263.4 and 262.4 (33.4 and 32.5) under homogeneous transport-mode and trade elasticities, respectively. These results indicate that imposing homogeneity in either elasticity can materially distort the cross-sectional pattern of counterfactual trade responses, with effects of broadly similar magnitude under the two



Notes: The figures show deviations, in percentage points, between scenarios with homogeneous transport-mode or trade elasticities and the benchmark case where both elasticities are heterogeneous. Panel A presents kernel density estimates of the deviations in welfare gains from trade, while Panel B presents the corresponding deviations in trade-share changes.

Figure 2: DEVIATIONS FROM THE FULLY HETEROGENEOUS BENCHMARK

assumptions.

Taken together, Panels A and B show that imposing a homogeneous transport-mode elasticity is at least as consequential for counterfactual outcomes as imposing a homogeneous trade elasticity. The effects are evident in both welfare and trade shares, indicating that sectoral heterogeneity in $\rho(s)$ materially shapes how economies adjust to transportation-cost shocks. Accounting for this heterogeneity is therefore quantitatively important for counterfactual analysis in trade models with endogenous transport-mode choice.

6 Conclusions

This paper develops an empirical framework to estimate sectoral transport-mode elasticities in international trade. Using newly available data and an instrumental-variables strategy, we provide comprehensive evidence on heterogeneity in sectoral responses to changes in mode-specific transportation costs. The estimated elasticities vary substantially across sectors and align closely with observable value-to-weight ratios.

To assess the quantitative relevance of this heterogeneity, we embed the estimated elasticities in a multi-country, multi-sector general-equilibrium model with endogenous transport-mode choice and input-output linkages. Counterfactual simulations of a 13% increase in international air-transport costs show that imposing a single transport-mode elasticity can substantially alter predicted ef-

fects on both welfare and trade flows. Moreover, the distortions from imposing a homogeneous transport-mode elasticity are broadly comparable to those generated by imposing a homogeneous trade elasticity. These results highlight the quantitative importance of sectoral heterogeneity in transport-mode adjustment for evaluating transportation-cost shocks.

References

- Aguiar, Angel**, "Concordances - six-digit HS sectors to GTAP sectors," *Global Trade Analysis Project (GTAP)*, 2016.
- , **Maksym Chepeliev**, **Erwin Corong**, and **Dominique van der Mensbrugghe**, "The Global Trade Analysis Project (GTAP) Data Base: Version 11," *Journal of Global Economic Analysis*, March 2023, 7 (2).
- Allen, Treb** and **Costas Arkolakis**, "Trade and the Topography of the Spatial Economy," *The Quarterly Journal of Economics*, May 2014, 129 (3), 1085–1140.
- and —, "The Welfare Effects of Transportation Infrastructure Improvements," *The Review of Economic Studies*, February 2022, 89 (6), 2911–2957.
- Anderson, James E.** and **Eric van Wincoop**, "Trade Costs," *Journal of Economic Literature*, September 2004, 42 (3), 691–751.
- ao, Nuno Lim** and **Anthony J. Venables**, "Infrastructure, Geographical Disadvantage, Transport Costs, and Trade," *The World Bank Economic Review*, October 2001, 15 (3), 451–479.
- Arkolakis, Costas**, **Arnaud Costinot**, and **Andrés Rodríguez-Clare**, "New Trade Models, Same Old Gains?," *American Economic Review*, February 2012, 102 (1), 94–130.
- Bernhofen, Daniel M.**, **Zouheir El-Sahli**, and **Richard Kneller**, "Estimating the effects of the container revolution on world trade," *Journal of International Economics*, 2016, 98, 36–50.
- Bertoli, Simone**, **Michael Goujon**, and **Olivier Santoni**, "The CERDI-seadistance database," Working Papers halshs-01288748, HAL March 2016.
- Besedeš, Tibor**, **Jing Chu**, and **Antu Panini Murshid**, "Fly the unfriendly skies: The role of transport costs in gravity models of trade," *Journal of International Economics*, 2024, 152, 103994.
- Brancaccio, Giulia**, **Myrto Kalouptsi**, and **Theodore Papageorgiou**, "Geography, Transportation, and Endogenous Trade Costs," *Econometrica*, 2020, 88 (2), 657–691.
- Caliendo, Lorenzo** and **Fernando Parro**, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, November 2014, 82 (1), 1–44.
- COMTRADE**, "United Nations Commodity Trade Statistics Database (UN Comtrade)," 2025.
- Cosar, A. Kerem** and **Banu Demir**, "Shipping inside the box: Containerization and trade," *Journal of International Economics*, 2018, 114, 331–345.
- Costinot, Arnaud** and **Andrés Rodríguez-Clare**, "Chapter 4 - Trade Theory with Numbers: Quantifying the Consequences of Globalization," in Gita Gopinath, Elhanan Helpman, and Kenneth

- Rogoff, eds., *Handbook of International Economics*, Vol. 4 of *Handbook of International Economics*, Elsevier, 2014, pp. 197–261.
- Dekle, Robert, Jonathan Eaton, and Samuel Kortum**, “Unbalanced Trade,” *American Economic Review*, May 2007, 97 (2), 351–355.
- Feyrer, James**, “Trade and Income—Exploiting Time Series in Geography,” *American Economic Journal: Applied Economics*, October 2019, 11 (4), 1–35.
- Fontagné, Lionel, Houssein Guimbard, and Gianluca Orefice**, “Tariff-based product-level trade elasticities,” *Journal of International Economics*, 2022, 137, 103593.
- Fuchs, Simon and Woan Foong Wong**, “Multimodal Transport Networks,” CEPR Discussion Paper 19531, Centre for Economic Policy Research (CEPR) 2024.
- Ganapati, Sharat, Woan Foong Wong, and Oren Ziv**, “Entrepôt: Hubs, Scale, and Trade Costs,” *American Economic Journal: Macroeconomics*, October 2024, 16 (4), 239–78.
- Harrigan, James**, “Airplanes and comparative advantage,” *Journal of International Economics*, 2010, 82 (2), 181–194.
- Hoffmeister, Onno, Ronald Halim, Nicholas-Joseph Lazarou, Nour Barnat, David Cristallo, Dominik Englert, and Jan Hoffmann**, “Developing a Global Transport Costs Dataset for International Trade,” *United Nations*, 2022.
- Hummels, David**, “Transportation Costs and International Trade in the Second Era of Globalization,” *Journal of Economic Perspectives*, September 2007, 21 (3), 131–154.
- Hummels, David L. and Georg Schaur**, “Time as a Trade Barrier,” *American Economic Review*, December 2013, 103 (7), 2935–59.
- Jaworski, Taylor and Carl T. Kitchens**, “National Policy for Regional Development: Historical Evidence from Appalachian Highways,” *The Review of Economics and Statistics*, December 2019, 101 (5), 777–790.
- , **Carl Kitchens, and Sergey Nigai**, “Highways and Globalization,” *International Economic Review*, 2023, 64 (4), 1615–1648.
- Lux, Matthias**, “Defying Gravity: The Substitutability of Transportation in International Trade,” MPRA Paper 36395, University Library of Munich, Germany May 2011.
- Mayer, Thierry and Soledad Zignago**, “Notes on CEPII’s distances measures: The GeoDist database,” Working Papers 2011-25, CEPII research center December 2011.
- Micco, Alejandro and Tomás Serebrisky**, “Competition regimes and air transport costs: The effects of open skies agreements,” *Journal of International Economics*, 2006, 70 (1), 25–51.

- Mikusheva, Anna and Liyang Sun**, “Weak identification with many instruments,” *The Econometrics Journal*, February 2024, 27 (2), C1–C28.
- Nigai, Sergey**, “Selection effects, inequality, and aggregate gains from trade,” *Journal of International Economics*, 2023, 142 (C).
- Söderlund, Bengt**, “The importance of business travel for trade: Evidence from the liberalization of the Soviet airspace,” *Journal of International Economics*, 2023, 145, 103812.
- Tolva, Edoardo**, “One Way or Another: Modes of Transport and International Trade,” mimeo, University of Warwick 2024.
- U.S. Bureau of Labor Statistics**, “Inbound Price Index (International Services): Air Freight,” <https://fred.stlouisfed.org/series/IC131> 2025. Accessed: 2025-07-11.
- , “Outbound Price Index (International Services): Air Freight,” <https://fred.stlouisfed.org/series/IS231> 2025. Accessed: 2025-07-11.
- Volpe Martincus, Christian and Juan Blyde**, “Shaky roads and trembling exports: Assessing the trade effects of domestic infrastructure using a natural experiment,” *Journal of International Economics*, 2013, 90 (1), 148–161.
- Wong, Woan Foong**, “The Round Trip Effect: Endogenous Transport Costs and International Trade,” *American Economic Journal: Applied Economics*, October 2022, 14 (4), 127–66.

Appendix

Table A1: SECTORAL AND COUNTRY COVERAGE

GTAP Sectors (65 sectors; 47 Manufacturing & 18 Services)
Manufacturing (47 sectors classified into 21 broad sectors): Agriculture and food processing (AFP) – [<i>Beverages and tobacco products (B.T), Bovine meat products (CMT), Bovine cattle, sheep and goats, horses (CTL), Sugar cane, sugar beet (C.B), Cereal grains n.e.c. (GRO), Dairy products (MIL), Animal products n.e.c. (OAP), Crops n.e.c. (OCR), Meat products n.e.c. (OMT), Oil seeds (OSD), Processed rice (PCR), Paddy rice (PDR), Plant-based fibers (PFB), Raw milk (RMK), Sugar (SGR), Vegetable oils and fats (VOL), Vegetables, fruits, nuts (V.F), Wheat (WHT), Wool, silk-worm cocoons (WOL)</i>]; Basic pharmaceutical products (BPH); Chemical products (CHM); Electrical equipment (EEQ); Computer, electronic and optical products (ELE); Energy (ENG) – [<i>Coal (COA), Electricity (ELY), Gas (GAS), Gas manufacture, distribution (GDT), Oil (OIL), Petroleum, coal products (P.C)</i>]; Metal products (FMP); Ferrous metals (I.S); Leather products (LEA); Motor vehicles and parts (MVH); Metals n.e.c. (NFM); Mineral products n.e.c. (NMM); Food products n.e.c. (OFD); Machinery and equipment n.e.c. (OME); Manufactures n.e.c. (OMF); Goods n.e.c. (OTH) – [<i>Forestry (FRS), Fishing (FSH), Wood products (LUM), Other Extraction n.e.c. (OXT)</i>]; Transport equipment n.e.c. (OTN), Paper products, publishing (PPP), Rubber and plastic products (RPP), Textiles (TEX), Wearing apparel (WAP). Services (18 sectors): Accommodation, Food, and Service Activities (AFS); Air Transport (ATP); Communication (CMN); Construction (CNS); Dwellings (DWE); Education (EDU); Human Health and Social Work (HHT); Insurance and Pension Services (INS); Business Services n.e.c. (OBS); Financial Services n.e.c. (OFI); Public Administration and Defense (OSG); Other Transport (OTP); Recreation and Other Services (ROS); Real Estate Activities (RSA); Trade (TRD); Warehousing and Support Activities (WHS); Water Transport (WTP); Water Collection, Treatment, and Supply (WTR).
Countries (153 in Estimation & 126 in Quantitative Model)
In Estimation and Quantitative Model (110 countries): Afghanistan (AFG); Albania (ALB); Algeria (DZA); Argentina (ARG); Armenia (ARM); Australia (AUS); Austria (AUT); Azerbaijan (AZE); Bahrain (BHR); Belarus (BLR); Belgium (BEL); Bolivia (BOL); Brazil (BRA); Bulgaria (BGR); Burkina Faso (BFA); Cambodia (KHM); Cameroon (CMR); Central African Republic (CAF); Chile (CHL); China (CHN); Colombia (COL); Costa Rica (CRI); Croatia (HRV); Cyprus (CYP); Czech Republic (CZE); Côte d'Ivoire (CIV); Denmark (DNK); Dominican Republic (DOM); Ecuador (ECU); Egypt (EGY); El Salvador (SLV); Estonia (EST); Eswatini (SWZ); Ethiopia (ETH); Finland (FIN); Georgia (GEO); Germany (DEU); Ghana (GHA); Greece (GRC); Guatemala (GTM); Honduras (HND); Hong Kong (HKG); Hungary (HUN); Indonesia (IDN); Iran (IRN); Ireland (IRL); Israel (ISR); Italy (ITA); Jamaica (JAM); Japan (JPN); Jordan (JOR); Kazakhstan (KAZ); Kenya (KEN); Kuwait (KWT); Kyrgyzstan (KGZ); Laos (LAO); Latvia (LVA); Lebanon (LBN); Lithuania (LTU); Luxembourg (LUX); Madagascar (MDG); Malawi (MWI); Malaysia (MYS); Malta (MLT); Mauritius (MUS); Morocco (MAR); Mozambique (MOZ); Namibia (NAM); Nepal (NPL); Netherlands (NLD); New Zealand (NZL); Nicaragua (NIC); Nigeria (NGA); Oman (OMN); Pakistan (PAK); Palestine (PSE); Panama (PAN); Paraguay (PRY); Peru (PER); Philippines (PHL); Poland (POL); Portugal (PRT); Qatar (QAT); Romania (ROU); Russia (RUS); Saudi Arabia (SAU); Serbia (SRB); Singapore (SGP); Slovakia (SVK); Slovenia (SVN); South Korea (KOR); Spain (ESP); Sri Lanka (LKA); Sudan (SDN); Sweden (SWE); Tajikistan (TJK); Tanzania (TZA); Thailand (THA); Trinidad and Tobago (TTO); Tunisia (TUN); Turkey (TUR); Uganda (UGA); Ukraine (UKR); United Arab Emirates (ARE); United Kingdom (GBR); Uruguay (URY); Uzbekistan (UZB); Vietnam (VNM); Zambia (ZMB); Zimbabwe (ZWE). Only in Estimation (43 countries): American Samoa (ASM); Bangladesh (BGD); Barbados (BRB); Belize (BLZ); Bermuda (BMU); Bhutan (BTN); Bosnia and Herzegovina (BIH); British Virgin Islands (VGB); Brunei (BRN); Canada (CAN); Cayman Islands (CYM); Chad (TCD); Cuba (CUB); Dominica (DMA); Fiji (FJI); French Polynesia (PYF); Gabon (GAB); Guyana (GUY); Haiti (HTI); Iceland (ISL); Iraq (IRQ); Libya (LBY); Macao (MAC); Mexico (MEX); Moldova (MDA); Montenegro (MNE); Myanmar (MMR); New Caledonia (NCL); North Macedonia (MKD); Papua New Guinea (PNG); Samoa (WSM); San Marino (SMR); Seychelles (SYC); Sierra Leone (SLE); Solomon Islands (SLB); South Africa (ZAF); Suriname (SUR); Syria (SYR); Tokelau (TKL); Tonga (TON); Turkmenistan (TKM); Venezuela (VEN); Yemen (YEM). Only in Quantitative Model (16 countries): Benin (BEN); Botswana (BWA); Comoros (COM); Democratic Republic of the Congo (COD); France (FRA); Guinea (GIN); India (IND); Mali (MLI); Mongolia (MNG); Niger (NER); Norway (NOR); Rwanda (RWA); Senegal (SEN); Switzerland (CHE); Togo (TGO); United States (USA).