International Transport costs:
New Findings from modeling additive costs
Online Appendix (Not for Publication)

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A. Three models: Comparison

The paper compares the empirical performances of two models: one with only ad-valorem costs (Model (A)) and one with where both ad-valorem and additive costs (Model (B)). For comparison purposes, we also estimate the model with only additive costs (Model (C)), in which case the estimated equation is:

$$\ln\left(\frac{p_{ik}}{\widetilde{p}_{ik}}-1\right)=\ln\left(\frac{t_i+t_{s(k)}}{\widetilde{p}_{ik}}\right)+\epsilon^{add}_{ik}$$

In this section, we first compare the estimates of the transport costs components under the three models. In a second step, we report quality of fit tests for the three models.

A.1. Estimation results

We report estimations of the three models for selected years. Section C provides estimations for every year. Table A.1 reports the results for air transport, Table A.2 for vessel transport.

Table A.1: Estimation results of the three models (Air, products at 5-digit level, sectors at 3-digit level)

	1974	1980	1990	2000	2010	2019
Data						
# obs.	14,955	16,118	24,958	35,027	40,284	44,133
# sectors	203	204	212	218	216	218
# origin countries	152	165	181	208	210	213
Observed transport costs						
Mean (in %)	5.3	4.0	4.1	2.8	3.1	2.3
Median (in %)	3.3	1.6	1.9	1.4	1.9	1.6
Std. dev.	6.7	6.4	6.0	4.8	5.2	3.6
Model (A)						
Multiplicative term ($\widehat{\tau}^{ice}-1$)						
Mean (in %)	6.9	5.4	5.0	3.6	4.2	3.0
Median (in %)	5.4	3.8	4.4	2.5	3.4	2.6
Std. dev.	5.2	4.9	3.9	3.3	3.7	2.3
Model (B)						
Multiplicative term ($\widehat{\tau}^{adv}-1$)						
Mean (in %)	3.6	2.3	2.4	1.7	2.6	2.0
Median (in %)	2.7	1.6	1.6	1.2	2.2	1.8
Std. dev.	3.2	2.5	2.1	1.6	2.3	1.5
Additive term ($\widehat{t}/\widetilde{p}$)						
Mean (in %)	2.6	2.0	1.8	1.3	1.1	0.6
Median (in %)	1.1	0.5	0.8	0.5	0.4	0.3
Std. dev.	4.0	4.1	3.3	2.8	2.4	1.7
Share of additive costs ($\widehat{\beta}$)						
Mean	0.34	0.33	0.33	0.31	0.21	0.19
Median	0.30	0.28	0.29	0.30	0.18	0.13
Std. dev.	0.24	0.23	0.21	0.20	0.18	0.19
Model (C)						
Additive term ($\widehat{t}^{add}/\widetilde{p}$)						
Mean (in %)	6.9	4.8	4.4	3.1	4.4	2.9
Median (in %)	4.4	1.8	2.3	1.4	2.7	1.6
Std. dev.	9.4	8.3	10.0	5.5	7.4	5.6

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs
Model (C): With additive transport costs only

Results for Models (A) and (B) are identical to those reported in the paper. Unsurprisingly, the estimated size of overall transport costs under Model (C) is of same order

Table A.2: Estimation results of the three models (Vessel, products at 5-digit level, sectors at 3-digit level)

	1974	1980	1990	2000	2010	2019
Data						
# obs.	19,007	17,356	28,383	36,093	37,748	41,137
# sectors	239	232	232	230	226	223
# origin countries	154	163	179	206	198	212
Observed transport costs						
Mean (in %)	8.9	6.2	5.4	5.3	4.2	4.1
Median (in %)	7.3	4.9	4.1	4.3	3.2	3.0
Std. dev.	6.7	5.0	4.8	4.7	3.6	3.5
Model (A)						
Multiplicative term ($\widehat{\tau}^{ice} - 1$)						
Mean (in %)	9.8	6.5	5.7	5.1	4.0	3.9
Median (in %)	9.6	5.5	4.6	4.8	3.5	3.8
Std. dev.	5.3	4.0	3.2	2.8	2.0	1.7
Model (B)						
Multiplicative term ($\widehat{\tau}^{adv} - 1$)						
Mean (in %)	5.4	3.1	3.3	2.5	1.9	2.0
Median (in %)	4.9	2.4	2.8	2.1	1.8	1.7
Std. dev.	4.1	2.3	2.2	2.1	1.7	1.4
Additive term ($\widehat{t}/\widetilde{p}$)						
Mean (in %)	5.1	3.4	2.8	2.8	2.5	2.2
Median (in %)	2.9	2.3	1.7	2.2	1.9	1.8
Std. dev.	8.5	4.6	4.1	4.3	2.5	2.3
Share of additive costs ($\widehat{\beta}$)						
Mean	0.41	0.50	0.39	0.51	0.54	0.50
Median	0.38	0.51	0.38	0.48	0.53	0.47
Std. dev.	0.30	0.25	0.21	0.28	0.30	0.25
Model (C)						
Additive term ($\widehat{t}^{add}/\widetilde{p}$)						
Mean (in %)	14.4	10.0	10.2	8.0	6.3	5.9
Median (in %)	9.5	6.7	6.3	4.9	4.6	4.3
Std. dev.	25.2	17.0	17.6	15.9	9.8	13.7

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs
Model (C): With additive transport costs only

of magnitude as in Models (A) and (B). We also observe a downward trend of transport costs over time, in particular since 1980.

A.2. Quality of fit diagnostic tests

To go further into the comparison of the empirical relevance of our three empirical models (A), (B) and (C), we compare quality of fit diagnostic tests in this section. Table A.3 reports the results for air transport, and Table A.4 those for vessel transport. In both tables, we report the values of the R^2, the Standard Error of Regression (SER), the AIC criterion and the log-likelihood (LL) value. We also report the value of the log-likelihood ratio that tests the quality of fit of the global model (Model (B)) compared to the other two models.

Table A.3: Quality-of-fit diagnostic tests, Air, 3-digit level

	1974	1980	1990	2000	2010	2019
$\boldsymbol{R^2}$						
Model (A)	0.44	0.48	0.46	0.47	0.42	0.28
Model (B)	0.59	0.65	0.63	0.64	0.51	0.37
Model (C)	0.49	0.54	0.52	0.52	0.34	0.26
SER (in %)						
Model (A)	4.7	4.5	4.1	3.4	3.7	2.9
Model (B)	3.8	3.2	3.0	2.1	2.7	2.3
Model (C)	6.8	5.2	8.1	2.7	4.7	4.3
AIC criteria						
Model (A)	35,672	41,166	60,718	87,494	102,297	123,708
Model (B)	31,386	35,740	52,099	74,955	95,887	118,554
Model (C)	40,795	45,149	69,448	100,126	129,293	148,246
Log-likelihood						
Model (A)	-17,498	-20,265	-29,976	-43,341	-50,747	-61,500
Model (B)	-15,114	-17,264	-25,393	-36,788	-47,278	-58,607
Model (C)	-20,055	-22,216	-34,349	-49,694	-64,251	-73,728
Test LL						
Stat LL ratio (B vs A)	4,768	6,001	9,166	13,105	6,938	5,787
# of restrictions (B vs A)	355	369	393	426	426	431
p-value (B vs A)	0.00	0.00	0.00	0.00	0.00	0.00
Stat LL ratio (B vs C)	9,882	9,905	17,911	25,811	33,948	30,242
# of restrictions (B vs C)	355	369	393	426	426	431
p-value (B vs C)	0.00	0.00	0.00	0.00	0.00	0.00

SER are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs
Model (C): With additive transport costs only

For all years and whatever the transport mode considered, the model with additive costs only (Model (C)) is consistently dominated (in terms of quality of fit properties) by the model with multiplicative costs only (Model (A)), which is itself consistently dominated by the complete model (Model (B)), whatever the type of diagnostic test considered. That justifies our choice to disregard Model (C) in the main text.

Table A.4: Quality-of-fit diagnostic tests, Vessel, 3-digit level

	1974	1980	1990	2000	2010	2019
R^2						
Model (A)	0.45	0.41	0.46	0.40	0.35	0.31
Model (B)	0.61	0.58	0.59	0.57	0.49	0.45
Model (C)	0.42	0.40	0.44	0.43	0.37	0.33
SER (in %)						
Model (A)	5.5	4.3	3.5	3.4	2.6	2.8
Model (B)	6.5	3.4	3.8	3.3	2.1	2.3
Model (C)	22.5	15.3	16.3	13.8	8.9	12.9
AIC criteria						
Model (A)	33,322	33,016	51,143	71,370	84,780	98,016
Model (B)	27,332	28,068	43,676	60,437	76,161	89,292
Model (C)	46,075	44,374	69,427	88,750	100,272	114,008
Log-likelihood						
Model (A)	-16,288	-16,129	-25,169	-35,264	-41,995	-48,600
Model (B)	-12,986	-13,356	-21,178	-29,480	-37,419	-43,967
Model (C)	-22,689	-21,814	-34,350	-43,963	-49,744	-56,616
Test LL						
Stat LL ratio (B vs A)	6,605	5,546	7,983	11,567	9,153	9,266
# of restrictions (B vs A)	393	395	411	436	424	435
p-value (B vs A)	0.00	0.00	0.00	0.00	0.00	0.00
Stat LL ratio (B vs C)	19,406	16,915	26,344	28,965	24,651	25,298
# of restrictions (B vs C)	393	395	411	436	424	435
p-value (B vs C)	0.00	0.00	0.00	0.00	0.00	0.00

SER are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs
Model (C): With additive transport costs only

B. Estimation at the 4-digit level

In this section, we report the estimation results when we retain the 4-digit classification level (s=4-digit).

B.1. Transport cost estimates

Tables B.4 and B.3 report the estimates of both models (with and without additive costs) in air and vessel transport respectively. Estimates at the 4-digit level confirm the significant role of the additive component in fitting international transport costs we found at the 3-digit level.

B.2. Goodness-of-fit tests at the 4-digit level

We now report the goodness-of-fit exercise (conducted by transport mode) at the 4-digit product classification level (for the selected years). The results are reported in Tables B.8 (for air) and B.7 (for vessel).

If anything, the quality of fit appears slightly higher when estimations are based on the 4-digit classification. This is especially true for the model restricting transport cost to their ad-valorem dimension, whatever the transport mode considered. When the additive part is taken into account however, the difference in goodness of fit between the 3- and the 4-digit classification level becomes very small, whatever the considered criterion. Using a more disaggregated product classification unsurprisingly adds some statistical precision, but the gain is not large enough to disqualify the use of slightly more aggregated data.

Table B.1: Air: Transport costs estimates, selected years, 4-digit level

Year	1974	1981	1989	2001	2009	2013
Model (A) ($\widehat{\tau}^{ice}-1$, in %)						
Mean	6.6	5.8	5.2	3.3	3.7	3.2
Median	5.2	4.4	4.1	2.1	2.7	2.6
Model (B)						
Ad-valorem term ($\widehat{\tau}^{adv}-1$, in %)						
Mean	3.5	2.6	3.1	1.5	2.1	1.6
Median	2.5	1.7	1.9	1.0	1.7	1.4
Additive term ($\widehat{t/\widetilde{p}}$), in %						
Mean	2.6	2.1	1.7	1.2	1.2	1.0
Median	1.2	0.6	0.6	0.5	0.4	0.4
# observations	14944	16844	25307	35005	38475	39460

Notes: TC = Transport Costs. Statistics are obtained weighting each observation by its share in trade (mode-dependent). Additive term expressed in fraction of fas price.

Table B.2: Air: Transport costs estimates, selected years, 4-digit level

	1974	1985	2005	2017	2019
Data					
# obs.	14,971	19,962	41,994	43,514	44,331
# sectors	488	554	637	631	635
# origin countries	152	169	212	212	213
Observed transport costs					
Mean (in %)	5.3	5.4	3.0	2.5	2.3
Median (in %)	3.3	2.6	1.4	1.4	1.5
Std. dev.	6.7	7.3	5.5	3.8	3.6
Model (A)					
Multiplicative term ($\widehat{\tau}^{ice}$)					
Mean (in %)	6.5	6.0	3.8	3.0	2.8
Median (in %)	5.2	4.9	2.7	2.5	2.0
Std. dev.	5.6	5.3	3.8	2.5	2.4
Model (B)					
Multiplicative term ($\widehat{\tau}^{adv}$)					
Mean (in %)	3.5	2.4	1.8	1.6	1.6
Median (in %)	2.5	1.6	1.2	1.5	1.3
Std. dev.	3.6	2.6	2.2	1.2	1.4
Additive term ($\widehat{t/\widetilde{p}}$)					
Mean (in %)	2.6	2.9	1.4	0.9	0.7
Median (in %)	1.2	1.4	0.5	0.4	0.3
Std. dev.	3.9	4.3	3.1	2.2	2.0
Elasticity of transport cost to price ($\widehat{\beta}$)					
Mean (in %)	0.35	0.45	0.33	0.25	0.28
Median (in %)	0.33	0.45	0.32	0.20	0.20
Std. dev.	0.24	0.22	0.22	0.19	0.24

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs

Table B.3: Vessel: Transport costs estimates, selected years, 4-digit level

Year	1974	1981	1989	2001	2009	2013
Model (A) ($\widehat{\tau}^{ice} - 1$, in %)						
Mean	9.8	6.1	5.8	5.1	4.2	3.6
Median	9.4	5.1	4.8	4.5	3.8	3.1
Model (B)						
Ad-valorem term ($\widehat{\tau}^{adv} - 1$, in %)						
Mean	5.4	3.4	2.8	2.8	2.4	2.1
Median	4.9	3.0	2.4	2.5	2.6	1.8
Additive term ($\widehat{t}^{add}/\widetilde{p}$, in %)						
Mean	4.6	2.6	3.1	2.4	2.1	1.5
Median	2.9	1.3	1.9	1.5	1.3	0.8
# observations	19196	17916	29387	36677	37643	38820

Notes: TC = Transport Costs. Statistics are obtained weighting each observation by its share in trade (mode-dependent). Additive term expressed in fraction of fas price.

Table B.4: Vessel: Transport costs estimates, selected years, 4-digit level

	1974	1985	2005	2017	2019
Data					
# obs.	19,201	23,603	41,773	40,992	41,484
# sectors	643	681	707	673	672
# origin countries	154	172	206	209	212
Observed transport costs					
Mean (in %)	9.0	6.5	5.4	4.0	4.1
Median (in %)	7.3	5.6	3.9	3.2	3.0
Std. dev.	7.1	5.3	5.0	3.3	3.5
Model (A)					
Multiplicative term ($\widehat{\tau}^{ice}$)					
Mean (in %)	9.8	7.1	5.5	3.7	3.9
Median (in %)	9.3	6.4	4.8	3.3	3.6
Std. dev.	6.0	4.3	3.0	2.0	1.9
Model (B)					
Multiplicative term ($\widehat{\tau}^{adv}$)					
Mean (in %)	5.4	3.8	2.7	2.3	1.9
Median (in %)	4.9	3.1	2.2	1.9	1.7
Std. dev.	4.3	3.2	2.2	1.3	1.4
Additive term ($\widehat{t}/\widetilde{p}$)					
Mean (in %)	4.6	3.3	2.9	1.6	2.2
Median (in %)	2.9	2.2	2.0	1.1	1.8
Std. dev.	6.8	4.0	3.6	2.1	3.0
Elasticity of transport cost to price ($\widehat{\beta}$)					
Mean (in %)	0.42	0.45	0.51	0.35	0.51
Median (in %)	0.43	0.43	0.49	0.37	0.47
Std. dev.	0.25	0.30	0.26	0.24	0.27

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs

Table B.5: Air: Measures of goodness of fit, 4-digit level

	Year					
	1974	1981	1989	2001	2009	2013
R^2						
Model (A)	0.48	0.49	0.50	0.50	0.45	0.35
Model (B)	0.63	0.66	0.65	0.66	0.54	0.45
SER						
Model (A)	0.8	0.9	0.83	0.87	0.88	0.93
Model (B)	0.67	0.74	0.69	0.80	0.80	0.86
Log-likelihood						
Model (A)	-17505.6	-21813.5	-30960.6	-44067.6	-49375.6	-53197.9
Model (B)	-14895.8	-18589.9	-26553.5	-37297.9	-45747.6	-49899.1
AIC criteria						
Model (A)	36243.1	44966.9	63417.1	89747.2	100317.13	107963.7
Model (B)	31873.6	39495.8	55777.1	77439.9	94059.1	102224.3
Test LL						
Stat LL ratio (B vs A)	5219.5	6447.1	8814.1	13539.4	7256.0	6597.5
# of restrictions (B vs A)	640	698	778	833	824	818
p-value (B vs A)	0.00	0.000	0.00	0.00	0.00	0.000

Notes: Model (A) = with only ad-valorem transport costs. Model (B) = with additive & ad-valorem transport costs. R^2 between the log of predicted ratio and the log of the observed ratio. The number # of restrictions is equal to the number of parameters estimated, i.e. the number of partner countries plus the number of products.

Table B.6: Air: Measures of goodness of fit, 4-digit level

	1974	1985	2005	2017	2019
R^2					
Model (A)	0.48	0.52	0.49	0.32	0.31
Model (B)	0.63	0.68	0.63	0.43	0.41
SER (in %)					
Model (A)	4.4	4.5	3.7	2.9	2.7
Model (B)	3.5	3.3	2.5	2.2	2.1
AIC criteria					
Model (A)	36,257	49,757	105,995	122,160	126,655
Model (B)	31,860	42,602	93,509	115,871	121,012
Log-likelihood					
Model (A)	-17,504	-24,181	-52,176	-60,268	-62,602
Model (B)	-14,897	-20,111	-45,319	-56,547	-59,145
Test LL					
Stat LL ratio (B vs A)	5,215	8,141	13,712	7,442	6,913
# of restrictions (B vs A)	640.0	723.0	849.0	843.0	848.0
p-value (B vs A)	0.00	0.00	0.00	0.00	0.00

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs

Table B.7: Vessel: Measures of goodness of fit, 4-digit level

	Year					
	1974	1981	1989	2001	2009	2013
R^2						
Model (A)	0.50	0.45	0.47	0.41	0.37	0.35
Model (B)	0.66	0.62	0.62	0.58	0.51	0.46
SER						
Model (A)	0.58	0.64	0.61	0.0.72	0.79	0.82
Model (B)	0.48	0.53	0.51	0.61	0.69	0.75
Log-likelihood						
Model (A)	-16460.1	-16951.6	-26771.4	-39008.3	-43888.9	-47161.6
Model (B)	-12743.65	-13546.9	-21752.8	-33281.0	-39078.9	-43399.2
AIC criteria						
Model (A)	34464.2	35491.2	55272.9	79800.7	89459.8	95987.2
Model (B)	28271.3	29877.8	46595.6	69743.9	81155.7	89692.4
Test LL						
Stat LL ratio (B vs A)	12385.80	11226.8	17354.7	20113.5	16608.2	12589.6
# of restrictions (B vs A)	797	814	881	910	886	874
p-value (B vs A)	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Model (A) = with only ad-valorem transport costs. Model (B) = with additive & ad-valorem transport costs. R^2 between the log of predicted ratio and the log of the observed ratio. The number # of restrictions is equal to the number of parameters estimated, i.e. the number of partner countries plus the number of products.

Table B.8: Vessel: Measures of goodness of fit, 4-digit level

	1974	1985	2005	2017	2019
R^2					
Model (A)	0.50	0.48	0.41	0.31	0.31
Model (B)	0.66	0.62	0.56	0.44	0.44
SER (in %)					
Model (A)	5.1	3.3	3.4	2.5	2.7
Model (B)	5.4	3.0	2.7	2.1	3.1
AIC criteria					
Model (A)	34,472	41,762	90,110	104,042	106,216
Model (B)	28,271	35,781	78,870	97,187	98,462
Log-likelihood					
Model (A)	-16,459	-20,066	-44,197	-51,177	-52,265
Model (B)	-12,744	-16,387	-37,838	-47,151	-47,762
Test LL					
Stat LL ratio (B vs A)	7,430	7,357	12,718	8,053	9,006
# of restrictions (B vs A)	797.0	853.0	913.0	882.0	884.0
p-value (B vs A)	0.00	0.00	0.00	0.00	0.00

Statistics are weighted by value
Model (A): Ad-valorem transport costs only
Model (B): With additive and ad-valorem transport costs

C. Transport Cost Estimates: Yearly Detailed Results

In this section, we complement Table 1 of the main text by reporting the year-to-year results of the estimation driven at the 3-digit classification level. Table C.1 reports the results for each year over 1974-2019 for vessel; Table C.2 reports similar results for air transport. In both cases, we report the estimated values of the transport costs (weighted mean and median) when only ad-valorem costs are modeled (Model (A)), when both additive and ad-valorem costs are modeled (Model (B)) and when only additive costs are modeled (Model (C)). In all tables, statistics are weighted by value.

Table C.1: Vessel: Transport costs estimates, all years, products at 5-digit level, sectors at 3-digit level

	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
Data														
# obs.	19,007	18,710	13,615	12,826	16,601	17,274	17,356	17,788	18,075	18,883	21,650	23,348	23,730	23,626
# sectors	239	239	227	191	234	237	232	231	231	231	232	232	233	234
# origin countries	154	151	160	162	161	164	163	165	160	157	160	171	172	171
Observed transport costs														
Mean (in %)	8.9	8.7	8.4	7.9	7.6	7.3	6.2	5.8	6.3	6.2	6.4	6.5	6.1	5.9
Median (in %)	7.3	7.2	7.0	6.5	6.6	5.9	4.9	4.8	5.2	5.1	5.4	5.6	4.5	4.5
Std. dev.	6.7	6.5	5.8	5.4	5.4	6.4	5.0	5.0	5.3	5.3	5.1	5.2	5.1	4.9
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$)														
Mean (in %)	9.8	9.9	8.9	8.3	8.1	7.5	6.5	6.0	6.3	7.0	7.0	7.0	6.7	6.2
Median (in %)	9.6	8.5	8.0	7.3	7.1	6.5	5.5	5.0	5.9	5.7	6.1	6.7	7.0	6.3
Std. dev.	5.3	7.3	4.1	3.8	4.1	3.9	4.0	3.3	3.3	3.8	3.5	3.6	3.5	3.1
Model (B)														
Mult. term ($\widehat{\tau}^{adv}$)														
Mean (in %)	5.4	4.8	5.4	3.9	5.9	4.6	3.1	3.3	3.4	4.6	4.1	4.0	3.9	3.5
Median (in %)	4.9	4.1	4.8	3.2	5.4	4.1	2.4	2.9	2.9	4.0	3.5	3.6	3.6	3.0
Std. dev.	4.1	4.7	2.7	3.0	3.1	2.6	2.3	2.3	2.5	2.6	2.8	2.9	2.7	2.3
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	5.1	5.5	3.5	4.8	2.5	3.1	3.4	2.9	3.5	2.5	3.2	3.2	2.9	2.9
Median (in %)	2.9	3.7	1.9	3.8	1.2	1.7	2.3	1.5	2.3	1.6	2.2	2.1	1.8	1.8
Std. dev.	8.5	7.1	5.4	6.2	4.2	4.8	4.6	4.6	5.5	4.2	4.5	3.9	4.1	4.1
Elasticity ($\widehat{\beta}$)														
Mean	0.41	0.47	0.31	0.52	0.24	0.34	0.50	0.38	0.46	0.28	0.41	0.42	0.38	0.40
Median	0.38	0.46	0.27	0.57	0.20	0.33	0.51	0.33	0.46	0.27	0.36	0.37	0.33	0.38
Std. dev.	0.30	0.31	0.23	0.28	0.23	0.27	0.25	0.28	0.28	0.22	0.27	0.27	0.26	0.24
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean (in %)	14.4	14.9	14.2	15.0	11.1	12.8	10.0	9.7	10.8	11.0	11.1	10.6	10.0	9.0
Median (in %)	9.5	10.5	8.4	8.5	6.7	7.2	6.7	6.7	6.8	7.1	7.2	7.4	7.3	6.6
Std. dev.	25.2	23.6	22.9	23.1	35.9	27.8	17.0	15.9	50.0	17.3	22.6	18.0	15.8	16.1

Table C.1: Vessel, Yearly estimates, Continued

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Data														
# obs.	27,662	29,106	28,383	28,095	29,050	30,839	31,865	32,146	32,344	33,182	33,986	34,585	36,093	36,407
# sectors	234	231	232	230	232	232	232	228	228	229	231	230	230	229
# origin countries	183	182	179	182	198	201	206	201	206	206	204	209	206	209
Observed transport costs														
Mean, in %	5.6	5.3	5.4	5.2	4.9	4.9	5.0	5.0	4.6	4.5	4.9	5.2	5.3	5.2
Median, in %	4.1	4.1	4.1	3.8	3.7	3.7	3.8	3.7	3.5	3.2	3.5	3.8	4.3	3.9
Std. dev.	5.0	4.7	4.8	4.6	4.5	4.5	4.6	4.8	4.3	4.3	4.6	4.5	4.7	4.7
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$)														
Mean (in %)	6.1	5.7	5.7	5.5	5.0	5.2	5.2	5.1	4.8	4.7	4.8	5.0	5.1	5.0
Median (in %)	5.7	4.8	4.6	4.4	4.2	4.6	4.1	4.3	3.9	3.9	3.9	4.5	4.8	4.6
Std. dev.	3.4	3.2	3.2	3.3	2.9	3.0	3.2	3.2	2.9	3.0	3.1	2.6	2.8	2.7
Model (B)														
Mult. term ($\widehat{\tau}^{adv}$)														
Mean (in %)	4.0	3.0	3.3	3.0	2.6	2.9	2.6	2.8	2.6	2.7	2.1	2.5	2.5	2.7
Median (in %)	3.5	2.6	2.8	2.7	2.3	2.6	2.2	2.5	2.2	2.3	1.8	2.1	2.1	2.6
Std. dev.	2.5	2.3	2.2	2.2	1.9	2.1	2.0	2.0	2.0	1.8	2.0	1.8	2.1	1.9
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	2.4	2.9	2.8	2.9	2.7	2.7	2.9	2.7	2.5	2.2	3.2	2.8	2.8	2.4
Median (in %)	1.3	2.0	1.7	1.8	1.8	1.6	2.0	1.8	1.6	1.3	2.0	2.0	2.2	1.6
Std. dev.	3.7	3.6	4.1	4.2	3.8	3.7	4.0	3.9	4.1	3.7	4.7	4.0	4.3	3.7
Share of additive costs ($\widehat{\beta}$)														
Mean	0.34	0.45	0.39	0.45	0.44	0.43	0.47	0.45	0.44	0.39	0.53	0.49	0.51	0.43
Median	0.34	0.42	0.38	0.44	0.46	0.40	0.45	0.45	0.43	0.38	0.47	0.46	0.48	0.43
Std. dev.	0.21	0.25	0.21	0.23	0.23	0.26	0.24	0.20	0.20	0.19	0.29	0.24	0.28	0.22
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean (in %)	8.9	8.6	10.2	9.1	8.1	8.1	8.4	8.4	8.0	8.0	8.2	8.0	8.0	7.8
Median (in %)	6.1	5.7	6.3	4.8	4.2	4.9	4.6	4.7	4.2	4.1	4.2	4.4	4.9	4.4
Std. dev.	17.9	18.3	17.6	15.6	13.3	12.2	13.7	15.4	15.0	14.9	15.8	14.2	15.9	14.4

Table C.1: Vessel, Yearly estimates, Continued

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Data														
# obs.	37,256	37,673	37,757	41,431	41,764	39,604	38,950	37,336	37,748	38,567	38,387	38,477	39,147	40,031
# sectors	229	229	230	229	231	227	228	226	226	227	223	224	225	225
# origin countries	206	211	210	206	207	207	199	207	198	202	203	203	203	204
Observed transport costs														
Mean (in %)	4.9	5.6	5.7	5.4	5.1	4.7	4.4	4.3	4.2	3.6	3.7	3.7	3.7	4.3
Median (in %)	3.8	4.5	4.8	3.9	3.7	3.6	3.6	3.5	3.2	2.6	2.9	2.6	2.8	3.3
Std. dev.	4.4	4.8	4.8	4.9	4.6	4.2	3.8	3.5	3.6	3.2	3.2	3.2	3.1	3.4
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$ -1)														
Mean, in %	4.8	5.3	5.4	5.4	4.8	4.7	4.4	4.3	4.0	3.5	3.6	3.6	3.5	3.9
Median, in %	4.1	4.9	5.0	4.9	4.3	4.2	3.8	4.1	3.5	3.0	3.1	3.3	2.9	3.3
Std. dev.	2.6	2.8	2.9	2.6	2.6	2.3	2.2	2.1	2.0	1.8	1.8	1.8	1.8	1.9
Model (B)														
Mult. term ($\widehat{\tau}^{adv} - 1$)														
Mean, in %	2.1	2.4	2.7	2.6	2.3	2.5	2.1	2.2	1.9	1.8	1.8	2.2	2.0	2.0
Median, in %	1.7	1.9	2.8	2.2	1.9	2.3	1.8	2.0	1.8	1.6	1.4	1.8	1.6	1.7
Std. dev.	2.1	2.3	2.1	2.2	2.0	2.0	2.0	1.7	1.7	1.5	1.5	1.2	1.4	1.4
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	2.9	3.2	2.9	3.0	2.8	2.4	2.4	2.1	2.5	1.9	1.9	1.5	1.6	2.1
Median (in %)	2.3	2.5	1.9	2.2	1.9	1.8	2.1	1.7	1.9	1.6	1.6	0.8	1.2	1.6
Std. dev.	3.4	4.1	4.2	3.4	3.8	3.0	2.8	2.4	2.5	2.0	2.0	2.0	1.9	2.2
Share of additive costs ($\widehat{\beta}$)														
Mean	0.56	0.55	0.47	0.53	0.54	0.49	0.54	0.48	0.54	0.54	0.52	0.33	0.41	0.47
Median	0.53	0.48	0.45	0.50	0.52	0.45	0.53	0.47	0.53	0.52	0.52	0.30	0.40	0.47
Std. dev.	0.27	0.29	0.27	0.28	0.27	0.27	0.29	0.25	0.30	0.30	0.25	0.21	0.25	0.23
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean, in %	8.0	8.3	8.1	8.4	7.5	7.0	6.6	6.4	6.3	5.4	5.2	5.2	5.2	6.0
Median, in %	4.7	5.2	5.3	5.7	5.1	4.6	5.3	4.5	4.6	3.9	3.5	3.3	3.2	4.2
Std. dev.	13.9	13.9	13.2	14.7	13.1	14.8	9.5	8.1	9.8	6.9	7.6	8.7	7.7	8.4

Table C.1: Vessel, Yearly estimates, Continued

	2016	2017	2018	2019
Data				
# obs.	40,569	40,647	41,118	41,137
# sectors	225	225	222	223
# origin countries	207	208	209	212
Observed transport costs				
Mean (in %)	4.1	4.0	4.0	4.1
Median (in %)	3.2	3.2	2.8	3.0
Std. dev.	3.3	3.2	3.9	3.5
Model (A)				
Mult. term ($\widehat{\tau}^{ice}$)				
Mean (in %)	3.9	3.7	3.6	3.9
Median (in %)	3.3	3.4	3.1	3.8
Std. dev.	1.8	1.9	1.6	1.7
Model (B)				
Mult. term ($\widehat{\tau}^{adv}$)				
Mean (in %)	2.3	2.4	2.0	2.0
Median (in %)	2.0	2.0	1.8	1.7
Std. dev.	1.5	1.3	1.3	1.4
Additive term ($\widehat{t}/\widetilde{p}$)				
Mean (in %)	1.8	1.6	1.8	2.2
Median (in %)	1.4	1.0	1.3	1.8
Std. dev.	1.8	1.9	2.0	2.3
Elasticity ($\widehat{\beta}$)				
Mean	0.41	0.33	0.43	0.50
Median	0.41	0.34	0.42	0.47
Std. dev.	0.24	0.21	0.25	0.25
Model (C)				
Additive term ($\widehat{t}^{add}/\widetilde{p}$)				
Mean (in %)	5.9	5.8	5.5	5.9
Median (in %)	4.1	4.1	3.7	4.3
Std. dev.	8.0	8.1	9.1	13.7

As mentioned in the paper, the estimates for air transport costs in 1989 show a surprisingly high value for the additive component (the additive cost is estimated to amount to 4.6% of the export price, whereas it amounts to 2.5% on average between 1974 and 1988, and to 1.7% over the following decade 1990-2000). This can be attributed to the presence of outliers in the distribution of the additive costs estimates, despite the exclusion of outliers in the data. The maximum value for $\widehat{t}/\widetilde{p}$ is 10,000% in 1989, whereas it amounts to 1,690% on average over 1974-1988 and to 1,500% on average over 1990-2000. Accordingly, in the paper we discard this year 1989 when we report the average values over the period of the transport costs estimates in air transport.
Excluding or excluding a single year out of 45 does not make much difference in the weighted mean transport cost.

Table C.2: Air: Transport costs estimates, all years, products at 5-digit level, sectors at 3-digit level

	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987
Data														
# obs.	14,955	15,299	11,397	10,707	15,222	15,684	16,118	16,864	17,322	18,181	20,644	19,908	20,695	20,793
# sectors	203	200	189	156	204	202	204	205	207	211	213	207	206	210
# origin countries	152	157	166	159	169	169	165	164	164	165	163	169	171	172
Observed transport costs														
Mean (in %)	5.3	6.0	6.0	6.8	5.3	4.6	4.0	4.5	4.6	5.1	5.5	5.4	5.7	5.8
Median (in %)	3.3	3.0	2.9	3.2	2.5	2.3	1.6	1.8	1.9	1.9	2.5	2.7	2.7	2.8
Std. dev.	6.7	7.7	7.5	8.4	7.2	6.3	6.4	6.8	7.0	7.6	7.9	7.3	7.6	7.7
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$)														
Mean (in %)	6.9	7.5	7.2	7.7	6.9	6.1	5.4	6.0	6.4	6.9	7.2	6.1	6.2	6.6
Median (in %)	5.4	6.4	6.9	7.2	6.3	5.3	3.8	4.8	5.4	6.1	6.9	5.5	5.5	6.3
Std. dev.	5.2	5.3	5.0	5.7	5.1	4.9	4.9	5.1	5.4	5.7	5.6	4.8	5.0	4.8
Model (B)														
Mult. term ($\widehat{\tau}^{adv}$)														
Mean (in %)	3.6	3.7	3.7	4.2	3.2	3.0	2.3	2.8	2.8	2.6	3.3	2.5	3.2	2.6
Median (in %)	2.7	2.6	2.8	3.0	2.1	2.4	1.6	1.8	1.9	1.9	2.7	1.8	2.1	2.0
Std. dev.	3.2	3.1	3.0	3.6	2.9	2.7	2.5	2.7	2.6	2.6	2.9	2.2	2.9	2.4
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	2.6	3.0	2.5	2.8	2.5	2.1	2.0	2.0	2.3	2.8	2.5	2.8	2.6	2.9
Median (in %)	1.1	1.2	1.0	1.2	1.0	0.7	0.5	0.6	0.8	1.0	1.0	1.3	1.2	1.4
Std. dev.	4.0	4.8	3.8	5.2	4.3	3.8	4.1	4.3	4.9	5.0	4.3	4.1	3.9	4.4
Elasticity ($\widehat{\beta}$)														
Mean	0.34	0.34	0.30	0.32	0.33	0.29	0.33	0.29	0.32	0.38	0.30	0.42	0.36	0.45
Median	0.30	0.28	0.29	0.28	0.28	0.24	0.28	0.26	0.30	0.41	0.28	0.41	0.34	0.45
Std. dev.	0.24	0.23	0.22	0.23	0.22	0.22	0.23	0.23	0.22	0.23	0.22	0.22	0.24	0.21
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean (in %)	6.9	7.6	7.1	8.1	6.6	5.6	4.8	5.2	5.5	6.2	6.2	6.0	6.5	6.2
Median (in %)	4.4	4.4	4.1	4.2	3.2	2.5	1.8	2.2	2.7	2.9	2.9	3.4	3.6	3.5
Std. dev.	9.4	10.3	11.7	13.4	27.1	9.5	8.3	9.9	10.7	10.1	9.8	8.4	9.8	8.7

Table C.2: Air, Vessel, Yearly estimates, Continued

	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001
Data														
# obs.	24,665	25,197	24,958	25,156	26,192	28,297	29,948	31,038	32,187	33,502	33,492	33,523	35,027	34,885
# sectors	217	213	212	213	214	216	214	217	217	224	221	219	218	219
# origin countries	186	185	181	180	200	200	206	207	208	207	211	208	208	210
Observed transport costs														
Mean (in %)	4.7	4.4	4.1	4.0	3.7	3.7	3.5	3.3	3.0	3.0	2.8	2.9	2.8	2.7
Median (in %)	2.2	2.0	1.9	1.8	1.6	1.8	1.6	1.7	1.5	1.5	1.5	1.4	1.4	1.3
Std. dev.	6.7	6.4	6.0	6.0	5.7	5.8	5.5	5.1	4.9	5.1	5.0	5.0	4.8	4.8
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$)														
Mean (in %)	5.7	5.3	5.0	5.1	4.9	5.1	4.6	4.6	4.2	4.1	3.8	3.8	3.6	3.5
Median (in %)	5.3	4.6	4.4	4.5	4.5	4.4	3.7	3.8	3.1	3.0	2.7	2.8	2.5	2.4
Std. dev.	4.3	4.1	3.9	4.1	3.9	4.0	3.8	3.5	3.5	3.5	3.5	3.4	3.3	3.4
Model (B)														
Mult. term ($\widehat{\tau}^{adv}$)														
Mean (in %)	3.1	3.1	2.4	2.7	2.2	2.3	2.2	2.1	1.9	1.8	1.8	1.7	1.7	1.6
Median (in %)	2.0	1.8	1.6	1.5	1.5	1.6	1.3	1.4	1.4	1.3	1.3	1.4	1.2	1.1
Std. dev.	2.9	2.7	2.1	2.5	2.1	2.1	2.1	1.8	1.9	1.9	1.8	1.7	1.6	1.8
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	1.7	4.6	1.8	1.8	1.9	1.9	1.7	1.6	1.5	1.5	1.4	1.4	1.3	1.3
Median (in %)	1.0	0.7	0.8	0.6	0.9	0.8	0.8	0.7	0.6	0.6	0.5	0.5	0.5	0.5
Std. dev.	2.9	168.6	3.3	4.2	3.6	3.7	3.5	3.4	3.1	2.8	3.0	2.9	2.8	2.8
Elasticity ($\widehat{\beta}$)														
Mean	0.33	0.29	0.33	0.32	0.36	0.34	0.36	0.34	0.32	0.36	0.34	0.33	0.31	0.35
Median	0.31	0.28	0.29	0.30	0.36	0.33	0.33	0.33	0.31	0.35	0.32	0.29	0.30	0.34
Std. dev.	0.22	0.22	0.21	0.23	0.22	0.21	0.23	0.20	0.20	0.20	0.19	0.20	0.20	0.20
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean (in %)	4.8	17.9	4.4	4.6	4.3	4.4	4.0	3.8	3.6	3.6	3.4	3.3	3.1	3.1
Median (in %)	2.4	2.3	2.3	2.2	2.1	2.0	1.7	1.7	1.6	1.7	1.6	1.6	1.4	1.4
Std. dev.	8.4	790.9	10.0	9.2	8.2	7.8	7.1	9.2	6.8	6.4	6.1	5.9	5.5	5.7

Table C.2: Air, yearly estimates, Continued

	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Data														
# obs.	35,161	35,891	36,991	41,806	42,554	40,859	40,164	38,279	40,284	41,191	40,912	40,049	40,683	42,311
# sectors	218	220	219	217	219	217	218	217	216	218	216	212	212	216
# origin countries	209	212	210	211	208	210	209	209	210	209	210	210	209	210
Observed transport costs														
Mean (in %)	3.2	3.1	3.1	3.1	2.8	3.0	3.1	2.8	3.1	3.0	2.7	2.5	2.5	2.6
Median (in %)	1.4	1.4	1.3	1.4	1.3	1.6	1.8	1.6	1.9	1.9	1.7	1.6	1.7	1.7
Std. dev.	5.8	5.5	5.5	5.5	5.2	5.5	5.3	4.8	5.2	4.6	4.3	4.0	3.8	3.9
Model (A)														
Mult. term ($\widehat{\tau}^{ice}$)														
Mean (in %)	3.8	3.9	4.0	4.1	3.9	4.1	4.1	4.0	4.2	3.9	3.7	3.4	3.2	3.2
Median (in %)	2.7	2.6	2.9	3.0	2.7	3.0	3.2	3.0	3.4	3.1	3.0	2.9	3.2	2.9
Std. dev.	3.8	3.7	3.6	3.6	3.5	3.7	3.6	3.6	3.7	3.4	3.2	2.4	2.2	2.2
Model (B)														
Mult. term ($\widehat{\tau}^{adv}$)														
Mean (in %)	1.6	1.9	1.9	2.0	1.8	2.3	2.3	2.3	2.6	2.2	2.2	1.7	1.7	1.9
Median (in %)	1.2	1.4	1.4	1.6	1.4	1.9	1.9	1.8	2.2	1.7	1.9	1.7	1.4	1.8
Std. dev.	1.8	1.9	2.0	1.9	2.1	2.3	2.3	2.3	2.3	2.2	2.1	1.2	1.1	1.3
Additive term ($\widehat{t}/\widetilde{p}$)														
Mean (in %)	1.6	1.4	1.5	1.4	1.3	1.2	1.2	1.2	1.1	1.1	0.9	1.0	1.0	0.8
Median (in %)	0.5	0.5	0.6	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.5	0.4	0.3
Std. dev.	3.5	3.2	3.0	3.0	2.7	2.6	2.6	2.5	2.4	2.2	1.9	2.0	1.9	1.7
Elasticity ($\widehat{\beta}$)														
Mean	0.36	0.30	0.33	0.29	0.31	0.24	0.24	0.23	0.21	0.24	0.24	0.27	0.27	0.20
Median	0.35	0.26	0.33	0.27	0.27	0.20	0.21	0.19	0.18	0.19	0.22	0.25	0.23	0.15
Std. dev.	0.21	0.19	0.20	0.21	0.21	0.18	0.18	0.19	0.18	0.20	0.18	0.20	0.21	0.17
Model (C)														
Additive term ($\widehat{t}^{add}/\widetilde{p}$)														
Mean (in %)	3.6	3.7	3.7	3.8	3.5	4.3	4.3	4.3	4.4	3.9	3.7	3.3	3.2	3.1
Median (in %)	1.7	1.7	1.7	1.9	1.6	2.4	2.4	2.3	2.7	2.4	2.3	2.1	2.0	1.7
Std. dev.	6.5	6.6	6.6	6.6	6.4	7.3	7.3	7.5	7.4	6.5	6.3	4.9	4.8	5.0

Table C.2: Air, yearly estimates, Continued

	2016	2017	2018	2019
Data				
# obs.	42,618	43,235	44,030	44,133
# sectors	220	219	217	218
# origin countries	213	212	212	213
Observed transport costs				
Mean (in %)	2.3	2.6	2.5	2.3
Median (in %)	1.6	1.4	1.6	1.6
Std. dev.	3.6	3.8	3.7	3.6
Model (A)				
Mult. term ($\widehat{\tau}^{ice}$)				
Mean (in %)	3.0	3.3	3.2	3.0
Median (in %)	2.3	3.0	2.9	2.6
Std. dev.	2.3	2.4	2.3	2.3
Model (B)				
Mult. term ($\widehat{\tau}^{adv}$)				
Mean (in %)	1.8	2.0	1.8	2.0
Median (in %)	1.7	1.9	1.7	1.8
Std. dev.	1.2	1.4	1.3	1.5
Additive term ($\widehat{t}/\widetilde{p}$)				
Mean (in %)	0.7	0.8	0.8	0.6
Median (in %)	0.2	0.4	0.3	0.3
Std. dev.	1.7	1.9	1.8	1.7
Elasticity ($\widehat{\beta}$)				
Mean	0.18	0.20	0.20	0.19
Median	0.16	0.13	0.14	0.13
Std. dev.	0.17	0.18	0.19	0.19
Model (C)				
Additive term ($\widehat{t}^{add}/\widetilde{p}$)				
Mean (in %)	2.7	3.0	3.0	2.9
Median (in %)	1.4	1.8	1.8	1.6
Std. dev.	5.0	5.1	5.7	5.6

D. Robustness checks

D.1. Variance decomposition exercise

In this section, we provide a variance decomposition exercise on the observed cif-fas price gap. Specifically, we determine the share of the observed variance in the ratio $\ln(\frac{\underline{p}_{ik}}{\widetilde{p}_{ik}} - 1)$ that comes from *i)* the between-product variance (at the 5-digit level, k) and *ii)* the between-sector variance (at the 3-digit level, s). The variance decomposition expression at the product level k (5-digit level) is obtained by applying the following formula (by year and transport mode):

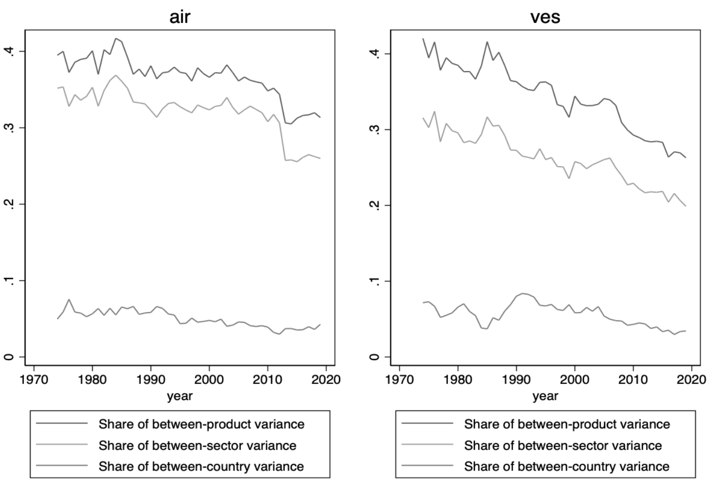
$$\sum_{k=1}^{K}\sum_{i=1}^{I}(x_{ik}-\bar{x}_g)^2 = \underbrace{\sum_{k}\sum_{i}(x_{ik}-\bar{x}_k)^2}_{(1)} + \underbrace{\sum_{k}(\bar{x}_k-\bar{x}_g)^2}_{(2)}$$

with x the observed cif-fas price gap and $\bar{x}_g$, $\bar{x}_k$ average values defined as:

$$\bar{x}_g \equiv \frac{1}{n}\sum_{k=1}^{K}\sum_{i=1}^{I}x_{ik}, \qquad \bar{x}_k \equiv \frac{1}{K}\sum_{k=1}^{K}x_{ik}$$

with n the total number of observations, K the total number of products and I the total number of country partners. In the above equation, the left-hand side gives the total variability, which decomposes into the within-product variability (Term (1)) and the between-product variability (Term (2)). We apply the same variance decomposition exercise at the sector level, in which case the sector s index (at the 3-digit level) replaces the k index (at the 5-digit level). This gives us an alternative way to ensure the robustness of the estimation results to the precision of the sector classification retained to estimate international transport costs. We also determine the share of the observed variance that can be attributed to the between-country variance, adapting the variance decomposition formula written above accordingly. Results are reported in Figure D.1.

Figure D.1: Variance decomposition (observed cif-fas price gap)



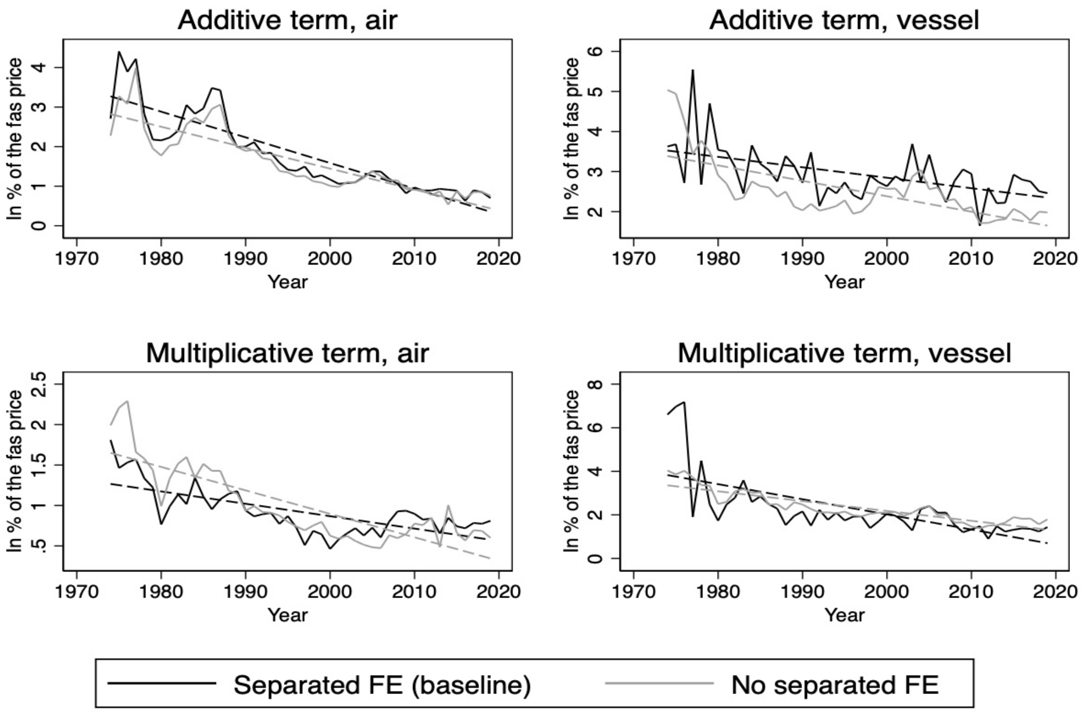
Two interesting results emerge from Figure D.1. First, the share of the cif-fas price gap variance that comes from the variance between products (5-digit level) is close to the variance between sectors at the 3-digit level. Both account for between 30 and 40% of the total variance in air transport, depending on the years considered. This is also the case for vessel transport, even if the difference between the between-product variance share and the between-sector share is larger (30% for the between-sector vs 40% for the between-product variance at the beginning of the period). This suggests our procedure should be robust to the choice of the precision of the sector classification. Second, the variance of the cif-fas price gap that can be attributed to the product (or sector) dimension is much larger than the between-country variance. This holds throughout the period and for both transport modes.

D.2. Separability Assumption

This section reports two supplementary checks concerning the separability assumption.

Comparison on a yearly basis. Figure D.2 displays the results on a yearly basis for air transport in panel (A) and for vessel transport in panel (B). In each case, the estimated values (as well as the regression line) under both separability (baseline) and non-separability are reported, for the additive term (upper panel) and the ad-valorem term (lower panel).

Figure D.2: Robustness to the separability assumption (year-to-year basis)



Notes: FE for (country, sector) fixed effects.

In line with Table 2 of the paper, Figure D.2 confirms that the separability assumption (retained in our baseline estimation) tends to overestimate the value of the additive cost component (and underestimate the value of the ad-valorem cost). However, it also shows that the difference is quantitatively small in most cases. Further, and most importantly, whatever the transport mode and for both types of transport costs, the trends, whether estimated under the separability assumption or not, are very similar. This confirms the robustness of our estimation results to this assumption.

D.3. Estimating $\widehat{\beta}_{i,s}$ directly

In this section, we explore an alternative estimation method, which proceeds as follows. β can be separately estimated for each industry s-origin country i using the following regression:

$$\ln TC_{ikd} = \beta_{is} \ln \tilde{p}_{ikd} + Z_{ikd} + \epsilon_{ikd} \tag{1}$$

where d denotes the US district of entry and k denotes an HS-10 product, TC_{ikd} being the transport costs and Z a set of controls variables. The identification of β_{is}, in this case, relies on exploiting the variability between sub-sectors at the 10-digit level (k) and between ports of entry in the US (d). From this, one can then recover the levels of additive and multiplicative transports costs. Denoting $\widehat{\beta}_{is(k)}$ the estimated β for a given sector-country $i, s(k)$, one can indeed solve the following two-equation system:

$$\begin{aligned} p_{ik} &= \tau_{is(k)}\widetilde{p}_{ik} + t_{is(k)} \\ \frac{t_{is(k)}}{(\tau_{is(k)} - 1)\widetilde{p}_{ik} + t_{is(k)}} &= \widehat{\beta}_{is(k)} \end{aligned}$$

with p_{ik} and $\widetilde{p}_{ik}$ the cif and fas prices observed in our dataset (conditional on a given year-transport mode).

One advantage of this approach is that the above equation is linear and can be estimated separately for various country-industry pairs, without having to resort on the separability assumption. Actually, it still requires a non-linear estimator due to the necessity of imposing an *ex-ante* restriction on parameters, i.e. imposing $0 \leq \beta \leq 1$. Should we relax this restriction, standard linear, least squares estimates often deliver negative, meaningless estimates. In this respect, the requirement of resorting on non-linear estimates (and the computational, time-consuming burden it induces) remains.

This estimation method also implies a lower coverage, both in time and in the sectors/countries covered. With respect to time coverage, information about the port of entry is only available since 1989, which is already smaller than our full sample starting in 1974. On top of that, because of the Covid situation, the US Bureau of Census was only able to provide us the data for the years 1997-1999 and 2001-2019. Using it would hence reduce the time coverage of our analysis by more than 20 years (skipping the 1974-1996 years in particular). In our view, the historical coverage is interesting *per se*: it provides useful insights about how transport costs have evolved over several decades and more importantly, it allows us to highlight the welfare alterations induced over the "hyper-globalization" period by the relative dynamics of additive and multiplicative costs.

With respect to the trade flows coverage, the method is run country by country, and 3-digit sector by 3-digit sector, exploiting the variability within each country-3d sector across 10-d sub-sectors and ports of entry. Yet, it appears that for many pairs (country, 3-digit sector), there is too few variability across sub-sectors or ports en entry given the number of fixed effects included in the regression, to estimate the equation.. This can be seen comparing the number of observations by year/ transport mode between this alternative method and our baseline method reported in Table D.1. Put differently, this methodology discards countries which export a limited range of goods to the US and/or which arrive in the USA through the same ports of entry. In this respect, the induced selection bias reduces the general scope of the transport costs estimates.

Notwithstanding these limitations, it remains interesting to run this alternative estimation method as robustness check. Table D.1 reports the estimation results, by transport mode, in the Column "Alternative", along with the results obtained with our baseline method over the same period 2005-2013. Figure D.3 displays the estimated share of additive costs β on a yearly basis over the estimation period, under both methods.

As noted above, the number of partners-sectors covered are lower. Regarding the share

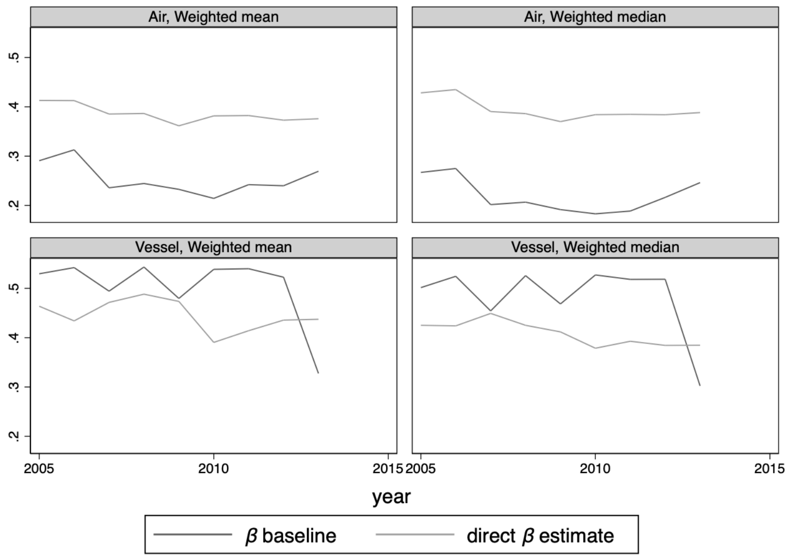
Table D.1: Baseline and direct β estimate, 2005-2013

Transport mode	Air		Vessel	
Estimation method	Alternative	Baseline	Alternative	Baseline
Coverage				
Nb sectors	177	217	203	227
Nb partners	112	210	123	204
Nb pairs	3,872	12,158	3,743	12,440
Annual covered value (Bn USD)	262	293	824	906
Share of additive costs β				
Mean	0.39	0.25	0.45	0.50
Median	0.39	0.22	0.41	0.48
Std. dev.	0.15	0.19	0.29	0.28
Time trend coefficient	-0.012	-0.020	-0.012	-0.031

Notes: Time trend coefficient is the annual growth rate.

of additive costs β, the comparison between the two methods delivers opposite conclusions depending on the transport mode. While the estimated β is lower for vessel transport with the alternative method (also displaying a larger decrease over the period), the opposite holds for Air transport. In any case, the share of additive costs remains substantial, around 40% on average across transport modes over the period, thereby confirming the main message of our paper regarding the importance of the additive component in international transport costs.

Figure D.3: Baseline and direct β estimate



If we take the value of the β by itself, there is no clear criteria to discriminate between the value estimated with the baseline method and estimating directly β (when, of course, run on the same sample). Further, as shown in Table D.1, there is no clear sign of a potential upwards or downwards bias that would be attached to either method. Things are more clear-cut in terms of accuracy of the estimation. Specifically, the baseline method yields a more precise estimation of the β than the direct method. To develop on this, for each year and transport mode:

- The direct method estimates one value for the share of additive component β at the i, s level denoted $\hat{\beta}^{dir}_{is(k)}$ associated with a standard deviation SD_{is}, by year and transport mode. From this, we can compute the size of the 5-95% confidence interval $CI^{dir}_{is} = \hat{\beta}^{max,dir}_{is} - \hat{\beta}^{min,dir}_{is}$ where:

$$\hat{\beta}^{min,dir}_{is} = \hat{\beta}^{dir}_{is(k)} - 1.96 SD_{is}, \quad \hat{\beta}^{max,dir}_{is} = \hat{\beta}^{dir}_{is(k)} + 1.96 SD_{is}$$

- The baseline method estimates the underlying trade costs components ($\widehat{\tau}_i$, $\widehat{\tau}_s$, $\widehat{t}_i$, $\widehat{t}_s$) with an associated matrix of variance-covariance, from which we can rebuild β_{is} (on a year-transport mode basis). As such, it does not yield an estimate of β_{is} and an associated standard deviation, so that we cannot directly compare the precision of the estimation. We compute the accuracy of the β estimation through a bootstrap method. Specifically, on a yearly/mode basis we draw a distribution of trade costs components and associated β_{is} (10,000 random draws) from which we can compute the mean, the median and the 5-95 confidence interval for each couple i, s. Writing β^{95}_{is} and β^{05}_{is} the associated thresholds, we then obtain the size of the confidence interval $CI_{is} = \beta^{95}_{is} - \beta^{05}_{is}$.[1]

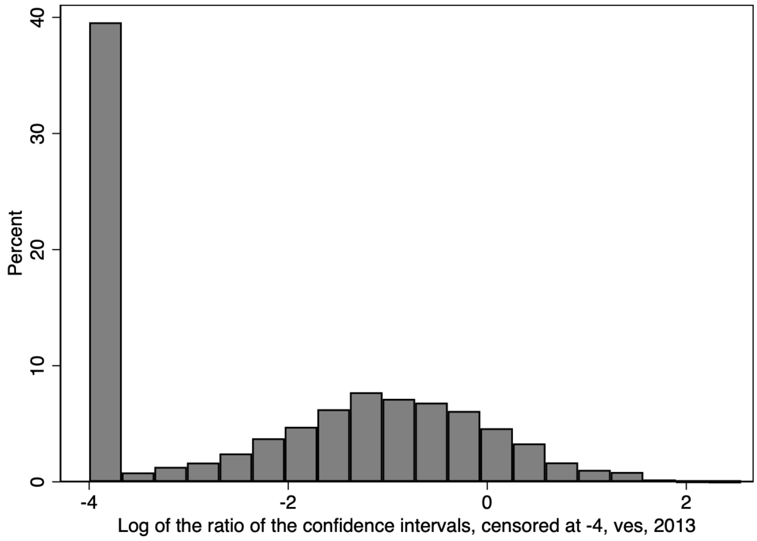
- We can then evaluate the accuracy of each method by comparing the size of the confidence intervals of the β, for each couple i, s (by year and transport mode). We summarize this comparison in Figure D.4, which reports the distribution of the ratio of confidence intervals, taken in log.

  XXXX AJouter le complement sur Air et stop XXX In most cases, the log of the ratio is negative, implying a smaller interval confidence of the baseline β estimation. Our method thus yields more accurate estimations of the share of additive components, whatever the transport mode considered. We have checked that a similar conclusion applies on other years (they are not reported here for sake of brevity but they are available upon request).

One explanation of the limited accuracy of the alternative method might be the following. Given that the estimation method is run at the country-sector level (exploiting heterogeneity *within* a given country-sector pair), it implicitly assumes that transport costs are independent *across* sectors and *across* origin countries. Put in plain words, it assumes that transport costs of say, cars, have nothing in common whether those goods comes from France or from Germany; or that transport costs that apply to imported goods from France have no common component across sectors. This is a disputable assumption. From a statistical point of view, it implies leaving aside information contained in the fact that transport costs have a both a country-specific component and a sector-specific component. We believe that explains the better accuracy of our baseline estimation.

[1] Notice that this should be made on the same sample as the one obtained with the direct method, since the goal is to compare the accuracy of the β_{is} estimate - implying to have the same sample of countries / sectors at first.

Figure D.4: Accuracy of the estimation of the β: Comparison



Note: Ratio of the confidence intervals = $ln(CI_{is}/CI_{is}^{ref})$

D.4. Weights and quantities

In the baseline method (as in most of the literature), the explained variable is a per-kg price rather than an unit price. Lashkaripour (2020) notably points out the importance of this issue. Based on US data very similar to ours over the period 1995-2015, the paper highlights, among other results, that the unit weight of imported goods is substantially heterogeneous even within narrowly-defined product categories and the cost of transportation increases more rapidly with unit weight than with the cost of production. Lashkaripour (2020) finds that accounting for the heterogeneity in export unit weights provides evidence in favor of the ad-valorem cost assumption regarding transport costs. This result of transport costs close to be totally ad-valorem contrasts from our own findings of additive costs representing 30 to 45% of total costs. There are explanations for this difference. Beyond a longer time span, our database is exhaustive, and encompasses all goods and industries, while Lashkaripour (2020) restricts to indivisible/discrete goods that represent a bit more than 56% of US total imports of goods in his dataset. In this regard, when comparing Tables 1 and 10 in Lashkaripour (2020), one can see that the share of multiplicative costs tends to decrease with the share of discrete goods. It is therefore reasonable to think that the inclusion of all goods, like in our setting, would move the average share of multiplicative costs far from 100%.

Nevertheless, this section investigates the robustness of our results when unit values are built as the ratio between value and quantity of goods per observation. We first discuss data and estimation difficulties before giving the results. At a more fundamental level, we argue that looking at transport costs on a per-weight basis does add relevant information.

Data availability issue. The first difficulty is availability of information on quantities. Neither the US Bureau of Census data nor the 1974-2004 Hummels's data (based on the Census Bureau data) report the quantity by transport mode. This is incompatible with our empirical strategy for estimation which is conditional on the transport mode, similarly as in Hummels (2007). As a result, computing the unit price of all trade flows would require the assumption that the weight per unit is the same for vessel shipments and air shipments at the level of the observation. This is unlikely, as one would expect the higher value-to-weight varieties to be transported by air rather than by vessel. The alternative is to consider only single-mode flows. In Hummels's data (1974-2014), on average 41.1 % of trade flows and 79% of trade value are multi-mode. Reducing the total value of the sample from 12,500 billion dollars to 2,650 billion dollars would entail a large loss of useful information. Original census data, when accessible, are more promising.[2] In 2019, multi-modal flows are 570 billion dollars out of 1,790 billion dollars, or 31% of the data. This is still a large share, but not too large to preclude any work. Accordingly, we dig deeper into this issue with the US Census dataset, restricting to single transport mode flows.

Quantity units are a second difficulty. The Census data remain silent on that matter. To the best of our knowledge, these can only be found in the "Harmonized Tariff Schedule of the United State". Unfortunately, these schedules change many time per year and only the schedules from 2009 onwards were available in a .csv format. On the years for which the match could be done (from 2009), it turns out that at our sector level (3-digit), goods (either at the 5-digit or the 10-digit level) are measured in different units. In 2019, only 125 3-digit sectors out of 230 are measured in a single unit (after cleaning up the unit names[3]).[4] Neglecting these differences would invalidate our functional forms, as no one expects the transport cost of a "piece" to be the same as the transport cost of a "kg", even in the same sector. So we are limited to using quantity units from 2009 to 2019, amending our structure of fixed effects to consider the triplet (origin country, sector, quantity unit).

Estimation issue. Getting deeper on the estimated functional form raised another difficulty in adapting our equation to per-unit rather than per-weight price. As discussed above, in our baseline regression we separate each transport cost component in two distinct sector-country dimensions. As in Irarrazabal et al. (2015), we assume an additive form for the additive cost, i.e. $t_{is(k)} = t_i + t_{s(k)}$ with i the origin country and s the sector. In the specific case of quantities, this raises a non-trivial issue for country-level fixed effects. Sector-level fixed effects could indeed be easily replaced by (sector times quantity unit) fixed effects; but the same does not appear possible for country fixed effects. Let us elaborate on this issue.

In the per-weight price, the existence of a single country fixed effect applicable to all sector could be justified, as a kilogram is always a kilogram and one can assume they both add the same to transport costs from, say, Germany. In contrast, an unit of tee-shirt is quite different from an unit of car. To clarify this point, consider imports of tee-shirts and cars from Germany and China. Under the separability assumption, importing a tee-shirt from either country implies paying the cost given by the country fixed effect (the same

[2] Original Census data are reported at the HS-10 digit × district of entry × district of unleading × rate provision code.

[3] As units are not always coherent (e.g. weight can be given in "kg", "kg." "Kg" and, also, "g" and "t").

[4] For instance, 3-digit SITC sector "061 Sugar, molasses and honey" includes among other products, 5-digit SITC product "6150 Molasses, whether or not decolourized", measured in liters and 5-digit SITC product "06160 Natural Honey" measured in kg. Even worse, the 5-digit SITC product "06190 Other sugars; sugar syrups; artificial honey (whether or not mixed with natural honey); caramel" includes both 10-digit HTS product "1702903500 Other: invert molasses", measured in liters and 10-digit HTS product "1702602200 Blended syrups described in additional u.s. note 4 to chapter 17: described in general note 15 of the tariff schedule and entered pursuant to its provisions" measured in kilograms.

for all sectors) plus the cost given by the sector fixed effect; and similarly for importing a car. Hence, the difference in the cost of importing a car from Germany versus China would be the same, in dollars, as the difference between the cost of importing a tee-shirt from Germany relative to China. This does not seem a sensible assumption. In this setting, we cannot keep the separability assumption. As discussed before, this dramatically increases the computational difficulty of our method (with no substantial different results, see Subsection 3.3.1. in the main paper.

Integrating these various constraints, we run the robustness check (weight versus quantity) *i)* on a sample reduced over 2009-2019, considering single transport mode flows - amounting to 66% of the value of the baseline sample; *ii)* retaining a non-separable structure of three-dimensional fixed effects $t_{is(k)u}$, $\tau_{is(k)u}$ according to the following equation:

$$\ln\left(\frac{p_{iku}}{\widetilde{p}_{iku}} - 1\right) = \ln\left(\tau_{is(k)u} - 1 + \frac{t_{is(k)u}}{\widetilde{p}_{iku}}\right) + \epsilon_{iku}$$

where p_{iku} refers to the cif price associated with quantity of goof k imported from country i, measured in unit u (e.g. kg or number), $\widetilde{p}_{iku}$ the corresponding unit value (fas price).

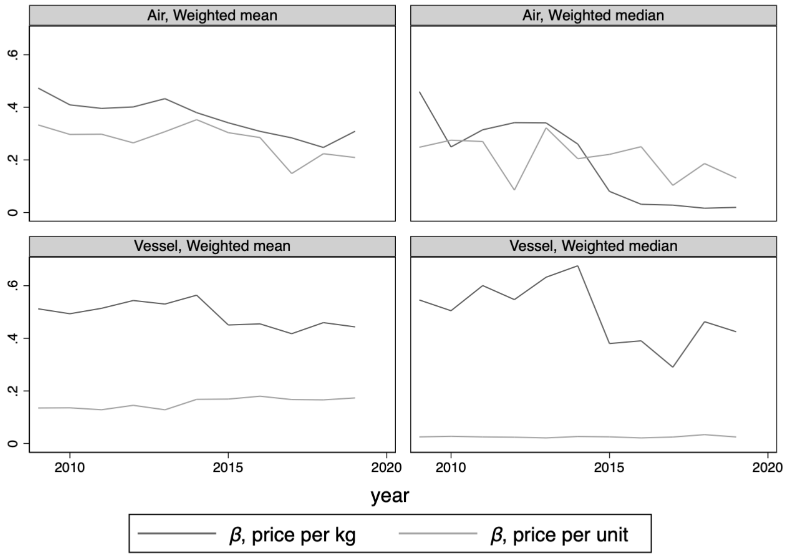
The results are reported in Table D.2 and in Figure D.5. In Table D.2, for each transport mode, the first column reports the estimation based on the price per quantity; while the second column reports the results obtained considering the price per kg on the same sample; the last column reported our baseline results on the large sample (considering the average value over 2005-2019, under the separability assumption).

Table D.2: Comparison Price per quantity or Price per kg, 2009-2019

Mode:	Air			Vessel		
Price per:	Qy	Kg	Kg	Qy	Kg	Kg
Sample	Limited	Limited	Baseline	Limited	Limited	Baseline
# of sectors	22	22	216	60	60	225
# of partners	15	15	211	21	21	205
# of pairs	339	339	12,544	1,100	1,100	12,649
Trade value (Bn USD)	242	242	331	583	583	920
Share of additive costs β						
Mean	0.27	0.36	0.22	0.15	0.49	0.45
Median	0.19	0.16	0.17	0.03	0.51	0.44
Std. dev.	0.29	0.39	0.19	0.25	0.29	0.26
Time trend coefficient	-0.049	-0.054	-0.026	0.032	-0.020	-0.022

Two main results emerge. First, given the constraints on the sample selection for quantities, the estimation based on quantity can only be run on a reduced sample. In contrast to the aggregation and the separability issues, these restrictions strongly limit both the number of sectors and of countries covered, and do also impact the value of trade flows covered. This raises a non-trivial sample selection bias that may reduce the general scope of the transport cost estimates. Second, in terms of β estimates, the results clearly show that using price per unit (whatever that unit is) instead of price per weight decreases the share of additive costs (except if one look at the median for air). In this respect, they stand in line with the results of Lashkaripour (2020), and confirm the correlation between weight per unit and unit price. Still, the share of additive cost is not reduced to zero (except if one looks at the median for vessel). Thus these results do not disqualify our approach,

Figure D.5: β Estimate: Price per quantity or price per kg, 2009-2019



Notes: In both cases, estimation is run without imposing the separability assumption.

especially as we cover a much larger period and sample with our baseline estimate.

On the relevance of the per-weight price approach. At a more fundamental level, we do believe that the study of transport costs measured on a per-weight price adds some relevant information on the international transport cost burden faced by exporters. We detail below why.

Our main objective in this paper is to provide a quantitative assessment of the international transport costs burden over time; on that matter, one may start with the observation that transport cost schedules are expressed through a mixed per-weight and per-volume basis, both historically and nowadays. For example, in 2021, air freight trade costs are expressed in weights, with a minimal weight per volume ("volumetric weight" or "dimensional weight")[5] while maritime freight costs are expressed in volume. Hence, looking at per-kg transport cost can be interpreted straightforwardly as trying to estimate the actual existing shipping costs, with sector fixed effects interpretable as measures of mean density for different sectors. The existence of per-volume or per-weight shipping cost is directly linked to the technical constraints of the transportation sector, hence exogenous to exporting firms' decisions - in contrast, per-unit shipping cost depends on the behavior of exporting firms. Put differently, the shipping cost per weight is one of the exogenous parameters firms take into account in their production choices, including weight per unit. Accordingly, studying the technical per-volume or per-weight shipping cost is interesting to understand the context in which they operate.

Another argument is illustrated by Figure D.6. After computing the share of discrete goods per 5-digit SITC import in 2009, we have used the changing composition of US

[5]See for example https://transporteca.co.uk/shipping-costs, http://wap.dhl.com/serv/volweight.html and https://en.wikipedia.org/wiki/Dimensional_weight).

imports to approximate the share of discrete goods in the total value of US imports on a yearly basis. According to this rough approximation, discrete goods are between 23% and 52% of US imports, reaching a value only above 50% for two years. Switching to a per-unit approach would hence mean a marked reduction in the trade flows coverage, thereby limiting the general scope of our estimates.

Figure D.6: Estimated share of discrete goods in US imports, 1974-2019

E. Eliminating the composition effects

E.1. More on the Hummels' methodology

This section complements Section 4 in the main paper, where we replicate the method adopted by Hummels (2007) on our database. Here, we report the raw measure of transport costs versus the "ceteris paribus" transport costs series, i.e. excluding composition effects, in percentage of the export price, as in Hummels (2007), for each transport mode. The parallel with Hummels's (2007) terminology stands as follows: In Figure E.1, the "transport costs, excluding composition effects" series refers to his "fitted ad-valorem rate"; the "raw transport costs" series refers to his "expenditure/import value". Unsurprisingly, this accords with his Figure 5 (for Air) and 6 (Vessel) for the same period (until 2014).

E.2. Composition effects: Primary vs. Manufacturing sector

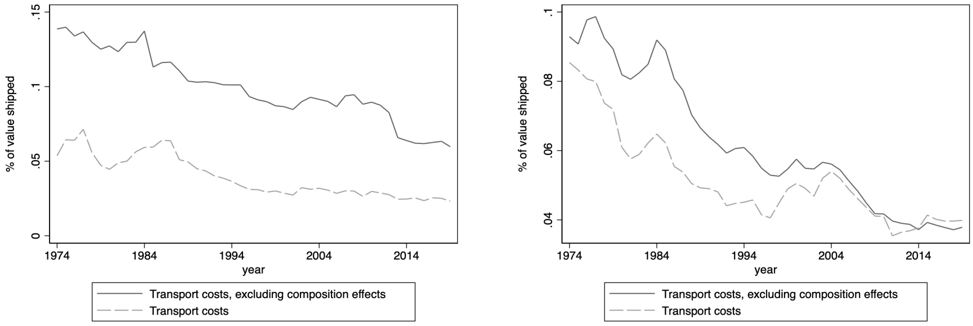
In this section, we refine the characterization of the evolution of international transport costs by distinguishing primary goods trade flows and and manufactured goods trade flows. The evolution in transport costs over time, by transport mode (overall transport costs and composition effects excluded) are reported in Figure E.2 for the manufacturing sector, and in Figure E.3 for the primary sector. To ease the comparison, we also report the results obtained on the whole range of trade flows (i.e., Figure 2 of the paper), in Figure E.4.

The classification retained to categorize trade flows follows the UNCTAD classification

Figure E.1: Characterizing the time trends: applying Hummels's (2007) method

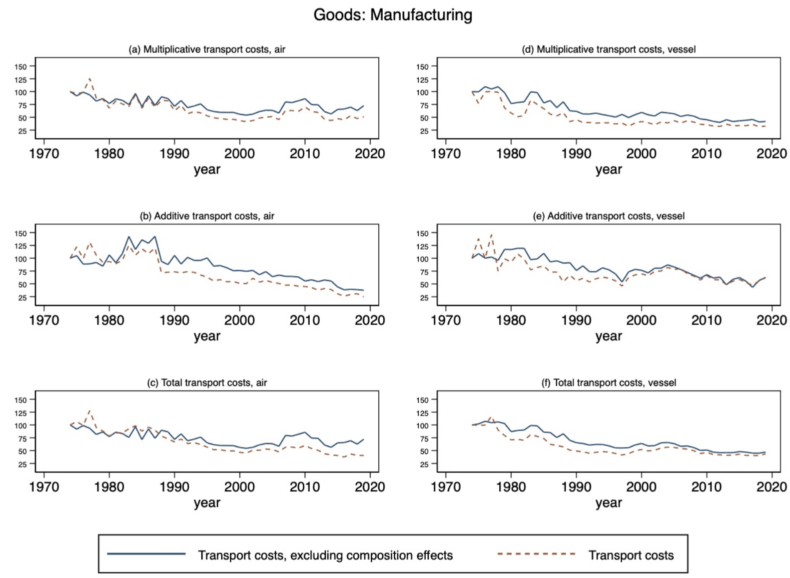
(A) Air (B) Vessel

In percent of value shipped (i.e. the export price)



(on STIC Revision 3)[6]. Are considered as "primary goods" all flows recorded as "Food and live animals" (First digit "0" in the SITC Classification), "Beverages and tobacco" (First digit "1"), "Crude materials, inedible, except fuels" (First digit "2"), "Mineral fuels, lubricants and related materials" (First digit "3"), "Animal and vegetable oils, fats and waxes" (First digit "4"), "Pearls, precious & semi-precious stones" (Classified "667" in the SITC Classification) and "Non-ferrous metals" (classified "68" in the SITC Classification).

Figure E.2: Transport costs (with and without composition effects), Manufacturing



As reported in Figures E.2 and E.3, both the "ceteris paribus" transport costs and the raw measure have regularly declined over the period in both sectors, by roughly the same

[6]See "UNCTAD product groupings and composition (SITC Rev. 3)" in http://unctadstat.unctad.org/EN/Classifications.html, accessed Septembre 2018

Figure E.3: Transport costs (with and without composition effects), Primary goods

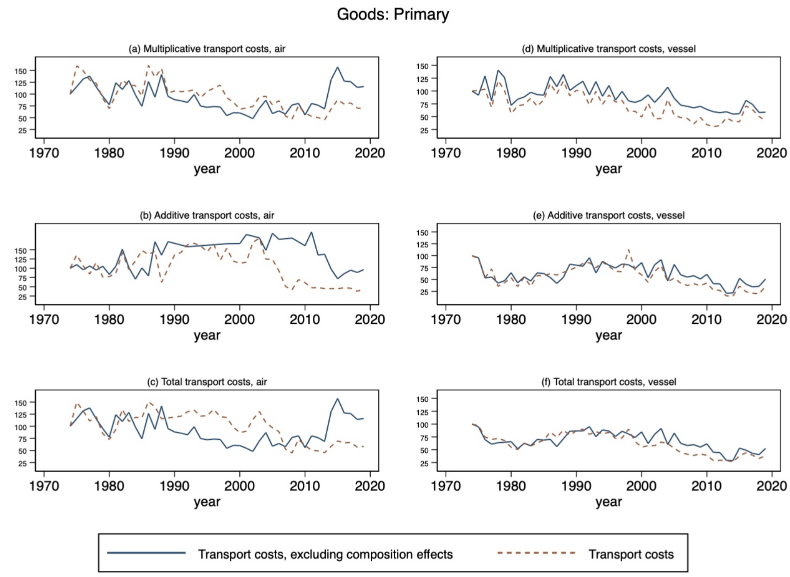
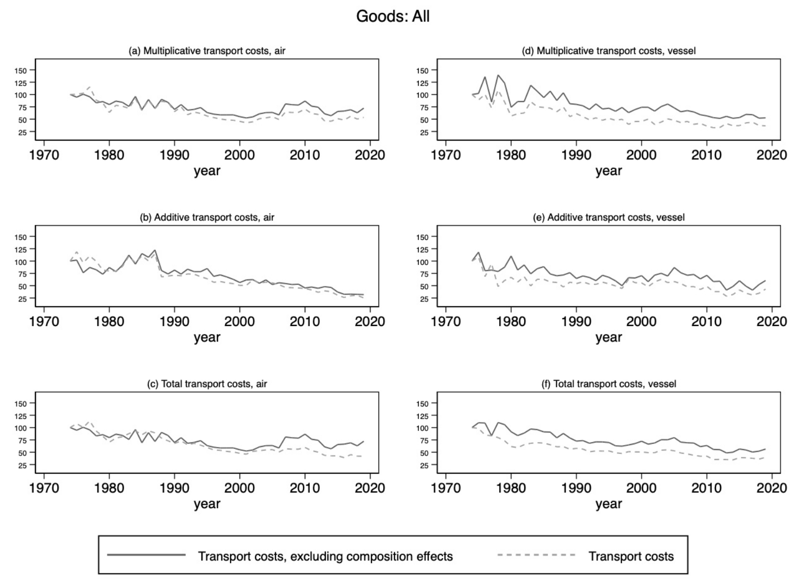


Figure E.4: Transport costs (with and without composition effects)

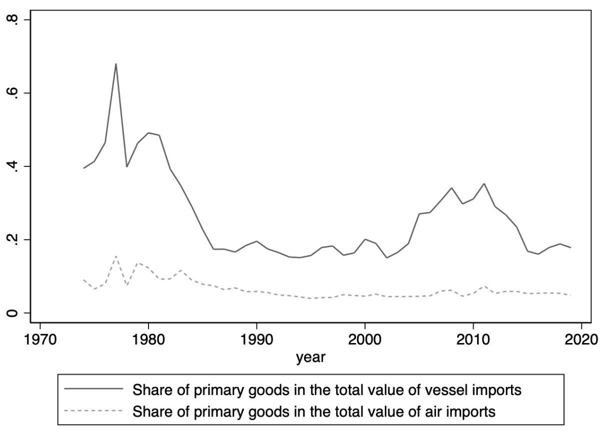


order of magnitude (50% in air, 60% in vessel for overall transport costs, panels (c) and (f)). However the role of trade composition effects in accounting for this trend pattern differs depending on the sector.
In the manufacturing sector, Figure E.2 reports a very similar time trend decomposition than what is obtained on the whole range of goods (Figure E.4). In vessel transport, most of the decrease can be imputed to the reduction of"ceteris paribus" transport costs (the blue continuous line): trade composition effects playing virtually no role (Figure E.2, right-hand panels (d), (e) and (f)). Trade composition effects matter more in air transport (Figure E.2, left-hand panels (a), (b) and (c)), primarily in the ad-valorem component. As for the whole range of flows, the 60% decrease in the raw transport costs in vessel can de decomposed in a 50% decrease in the "ceteris paribus" transport costs, the 10% remaining to trade composition effects.

The situation is similar in the primary sector. In this case, in air transport te composition effect matters more (Figure E.3, left-hand panels (a), (b) and (c)), while we observe not much role for them in vessel transport (Figure E.3, right-hand panels (d), (e) and (f)).

One explanation for the similarity between the results for the manufacturing goods trade and for total trade can be found in the share of primary goods in total flows as reported in Figure E.5. In air transport, the share of primary goods in the total value of US imports is very small, around 10%. Primary goods make a higher proportion of trade flows in vessel transport, especially over 1974-1982 (between 40% and 60%). On the following sub-period though, their share has fallen to 20-30%. Given the modest proportion of primary goods in total import flows of the US economy compared to the manufactured sector, it is not surprising that the diagnosis made about the time trend of transport costs when all types of flows are considered is driven by the manufacturing sector.

Figure E.5: Share of primary goods in the value of total US imports



References

Hummels, D. (2007). Transportation costs and international trade in the second era of globalization. *Journal of Economic Perspectives*, 21(3), 131–154.

Irarrazabal, A., Moxnes, A., & Opromolla, L. D. (2015). The tip of the iceberg: A quantitative framework for estimating trade costs. *The Review of Economics and Statistics*, 97(4), 777–792.

Lashkaripour, A. (2020). Weight-based quality specialization. *Journal of International Economics*, 127, 103380.