Implications of an antagonist age for maritime trade and its impacts on energy demand

Supplementary Information

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Contents

1. Ordinary least squares regression results

For the calculation of the historical coefficients, we use an ordinary least squares (OLS) regression. We utilize the R-package GME for it[1]. Most of the coefficients are significant on a 95% confidence interval. We still use the ones that are not significant on a 95% interval in this study as we are modeling a paradigm shift in international trade and, thus, a diverting future from history.

In Table S1 we show the overview of the used coefficients. A detailed description of all of the regression results is enclosed after the summary table.

Table S1: Summary of OLS regression results

Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Bulk Carrier				
Distance (log)	-0.6307	-1.0699	0.1959	-1.1264
Population Origin (log)	0.507	0.0741	0.721	-0.0278
Population Destination (log)	-0.1634	0.2178	0.185	0.2007
GDP Origin (log)	0.2067	0.713	0.7945	0.7741
GDP Destination (log)	0.9656	0.5936	-0.015	0.606
Democracy Index Origin	2.3491	-0.1341	3.7397	1.1226
Democracy Index Destination	-2.245	-0.4698	-0.7599	-1.3393
Intercept	-10.1386	-8.7039	-17.5774	-8.4341
Chemical Tanker				
Distance (log)	-0.9191	-0.3969	-1.2876	-0.9473
Population Origin (log)	-0.6569	-0.5967	0.1251	-0.5941
Population Destination (log)	0.0158	0.2386	0.1238	0.0538
GDP Origin (log)	1.3552	1.4374	0.8001	1.2264
GDP Destination (log)	0.8964	0.5569	0.8289	0.8439
Democracy Index Origin	-0.9074	1.0733	-0.7694	-0.4845
Democracy Index Destination	-0.8923	0.6347	0.338	1.11
Intercept	-19.0483	-22.1093	-13.4575	-16.277
Containers				
Distance (log)	-0.9725	-0.2907	-0.9515	-1.2906
Population Origin (log)	0.0844	0.3362	0.0414	-0.1932
Population Destination (log)	0.0503	0.0563	-0.1052	-0.1408
GDP Origin (log)	0.7805	0.6261	0.7783	1.1232
GDP Destination (log)	0.8614	0.8977	0.8395	0.6869
Democracy Index Origin	-0.2965	-1.9884	0.0999	-0.6679
Democracy Index Destination	-0.6645	-0.1652	0.5029	0.0635
Intercept	-11.9286	-18.5967	-10.0393	-7.6575
Oil Tanker				
Distance (log)	-1.1293	-0.9463	-0.7469	-0.5708
Population Origin (log)	-0.2175	-0.8467	0.3807	-0.7233
Population Destination (log)	0.2558	0.2147	-0.4738	-0.2563
GDP Origin (log)	0.9495	0.981	0.4277	0.9048
GDP Destination (log)	0.8617	0.6447	1.2286	1.0587
Democracy Index Origin	-4.8446	-4.827	-2.6091	-3.1308
Democracy Index Destination	-0.6807	0.6936	3.7248	2.3886
Intercept	-12.0214	-3.9738	-13.1849	-10.2629
LNG Carrier				
Distance (log)	-1.1744	-1.8642	-1.2264	-1.2165
Population Origin (log)	-0.6557	-0.7084	1.2666	-0.6475
Population Destination (log)	-0.3443	-0.354	-0.6371	-0.0295
GDP Origin (log)	1.1149	0.5349	-0.2858	0.2871
GDP Destination (log)	1.5059	1.319	1.5527	0.7382
Democracy Index Origin	-3.4243	-5.6891	1.3958	-7.3816
Democracy Index Destination	-4.7192	-4.7913	2.2201	1.8988
Intercept	-17.1001	5.0634	-13.5476	8.1648
Ro-Ro				
Distance (log)	-0.9434	-0.5778	-0.7978	-0.8745
Population Origin (log)	0.1733	-0.2598	0.1419	-0.3038
Population Destination (log)	0.1367	0.431	-0.3898	-0.374
GDP Origin (log)	0.9173	1.1936	0.9116	1.2473
GDP Destination (log)	0.9227	0.3727	1.0803	0.6188
Democracy Index Origin	-0.8411	1.5967	1.0049	0.9736
Democracy Index Destination	0.1584	1.0939	0.006	1.1663
Intercept	-19.8565	-17.8835	-19.0708	-11.3147

Model:	GLM	AIC:	8952593878.5497
Link Function:	Log	BIC:	8952149616.4829
Dependent Variable:	bulk dry_value	Log-Likelihood:	-4.4763e+09
Date:	2023-02-13 10:56	LL-Null:	-9.7183e+09
No. Observations:	20727	Deviance:	8.9524e+09
Df Model:	7	Pearson chi2:	2.47e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

Bulk Carrier - Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.6307	0.0261	-24.1300	0.0000	-0.6819	-0.5795
pop_o_log	0.5070	0.0497	10.1923	0.0000	0.4095	0.6045
pop_d_log	-0.1634	0.0415	-3.9345	0.0001	-0.2448	-0.0820
gdp_d_log	0.9656	0.0449	21.5185	0.0000	0.8776	1.0535
gdp_o_log	0.2067	0.0437	4.7271	0.0000	0.1210	0.2924
democracy_o	2.3491	0.2600	9.0355	0.0000	1.8396	2.8587
democracy_d	-2.2450	0.2780	-8.0760	0.0000	-2.7899	-1.7002
intercept	-10.1386	0.7079	-14.3225	0.0000	-11.5260	-8.7512

Model:	GLM	AIC:	1212901304.0978
Link Function:	Log	BIC:	1212729106.1431
Dependent Variable:	bulk dry_value	Log-Likelihood:	-6.0645e+08
Date:	2023-02-13 10:56	LL-Null:	-1.9045e+09
No. Observations:	9283	Deviance:	1.2128e+09
Df Model:	7	Pearson chi2:	2.30e+09
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

Bulk Carrier - Cluster 2	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.0699	0.0385	-27.7851	0.0000	-1.1454	-0.9945
pop_o_log	0.0741	0.0333	2.2228	0.0262	0.0088	0.1395
pop_d_log	0.2178	0.0522	4.1733	0.0000	0.1155	0.3200
gdp_d_log	0.5936	0.0499	11.8886	0.0000	0.4957	0.6914
gdp_o_log	0.7130	0.0338	21.1062	0.0000	0.6468	0.7792
democracy_o	-0.1341	0.1274	-1.0526	0.2925	-0.3837	0.1156
democracy_d	-0.4698	0.3626	-1.2957	0.1951	-1.1804	0.2408
intercept	-8.7039	0.6657	-13.0744	0.0000	-10.0087	-7.3991

Model:	GLM	AIC:	5342098884.0233
Link Function:	Log	BIC:	5341910717.5469
Dependent Variable:	bulk dry_value	Log-Likelihood:	-2.6710e+09
Date:	2023-02-13 10:56	LL-Null:	-6.8577e+09
No. Observations:	9317	Deviance:	5.3420e+09
Df Model:	7	Pearson chi2:	1.30e+10
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

Bulk Carrier - Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	0.1959	0.0504	3.8875	0.0001	0.0971	0.2947
pop_o_log	0.7210	0.1018	7.0809	0.0000	0.5215	0.9206
pop_d_log	0.1850	0.0336	5.5100	0.0000	0.1192	0.2508
gdp_d_log	0.7945	0.0501	15.8547	0.0000	0.6963	0.8927
gdp_o_log	-0.0150	0.0701	-0.2140	0.8305	-0.1524	0.1224
democracy_o	3.7397	0.3387	11.0420	0.0000	3.0759	4.4035
democracy_d	-0.7599	0.2519	-3.0167	0.0026	-1.2536	-0.2662
intercept	-17.5774	1.1601	-15.1513	0.0000	-19.8512	-15.3036

Model:	GLM	AIC:	799405459.2394
Link Function:	Log	BIC:	799332221.9612
Dependent Variable:	bulk dry_value	Log-Likelihood:	-3.9970e+08
Date:	2023-02-13 10:57	LL-Null:	-1.1347e+09
No. Observations:	3815	Deviance:	7.9936e+08
Df Model:	7	Pearson chi2:	1.23e+09
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

Bulk Carrier - Cluster 4	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.1264	0.0437	-25.7631	0.0000	-1.2121	-1.0407
pop_o_log	-0.0278	0.0306	-0.9077	0.3641	-0.0878	0.0322
pop_d_log	0.2007	0.0378	5.3107	0.0000	0.1266	0.2747
gdp_d_log	0.6060	0.0426	14.2299	0.0000	0.5226	0.6895
gdp_o_log	0.7741	0.0402	19.2620	0.0000	0.6953	0.8529
democracy_o	1.1226	0.2156	5.2067	0.0000	0.7000	1.5452
democracy_d	-1.3393	0.2489	-5.3799	0.0000	-1.8272	-0.8514
intercept	-8.4341	0.9063	-9.3061	0.0000	-10.2104	-6.6578

Model:	GLM	AIC:	4193907108.0557
Link Function:	Log	BIC:	4193491021.1992
Dependent Variable:	chemical_value	Log-Likelihood:	-2.0970e+09
Date:	2023-02-13 10:56	LL-Null:	-7.5880e+09
No. Observations:	20727	Deviance:	4.1937e+09
Df Model:	7	Pearson chi2:	1.23e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

Chemical Tanker - Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.9191	0.0228	-40.2571	0.0000	-0.9638	-0.8743
pop_o_log	-0.6569	0.0501	-13.1199	0.0000	-0.7550	-0.5587
pop_d_log	0.0158	0.0354	0.4452	0.6562	-0.0537	0.0852
gdp_d_log	0.8964	0.0329	27.2159	0.0000	0.8319	0.9610
gdp_o_log	1.3552	0.0378	35.8488	0.0000	1.2811	1.4293
democracy_o	-0.9074	0.2261	-4.0128	0.0001	-1.3506	-0.4642
democracy_d	-0.8923	0.2835	-3.1475	0.0016	-1.4480	-0.3367
intercept	-19.0483	0.4967	-38.3516	0.0000	-20.0218	-18.0748

Model:	GLM	AIC:	1203679247.4905
Link Function:	Log	BIC:	1203518746.2254
Dependent Variable:	chemical_value	Log-Likelihood:	-6.0184e+08
Date:	2023-02-13 10:56	LL-Null:	-1.7237e+09
No. Observations:	9283	Deviance:	1.2036e+09
Df Model:	7	Pearson chi2:	2.58e+09
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

Chemical Tanker - Cluster 2	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
distw_log	-0.3969	0.0410	-9.6828	0.0000	-0.4773	-0.3166
pop_o_log	-0.5967	0.0438	-13.6274	0.0000	-0.6825	-0.5109
pop_d_log	0.2386	0.0473	5.0390	0.0000	0.1458	0.3313
gdp_d_log	0.5569	0.0395	14.0854	0.0000	0.4794	0.6344
gdp_o_log	1.4374	0.0432	33.2646	0.0000	1.3528	1.5221
democracy_o	1.0733	0.1830	5.8636	0.0000	0.7145	1.4320
democracy_d	0.6347	0.2688	2.3608	0.0182	0.1078	1.1616
intercept	-22.1093	0.7518	-29.4067	0.0000	-23.5829	-20.6357

Model:	GLM	AIC:	785952923.4815
Link Function:	Log	BIC:	785784189.4690
Dependent Variable:	chemical_value	Log-Likelihood:	-3.9298e+08
Date:	2023-02-13 10:56	LL-Null:	-1.8779e+09
No. Observations:	9317	Deviance:	7.8587e+08
Df Model:	7	Pearson chi2:	3.14e+09
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

Chemical Tanker - Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.2876	0.0555	-23.2180	0.0000	-1.3963	-1.1789
pop_o_log	0.1251	0.0734	1.7041	0.0884	-0.0188	0.2690
pop_d_log	0.1238	0.0602	2.0580	0.0396	0.0059	0.2417
gdp_d_log	0.8289	0.0533	15.5398	0.0000	0.7244	0.9335
gdp_o_log	0.8001	0.0735	10.8903	0.0000	0.6561	0.9441
democracy_o	-0.7694	0.4945	-1.5558	0.1197	-1.7387	0.1999
democracy_d	0.3380	0.1893	1.7851	0.0742	-0.0331	0.7091
intercept	-13.4575	1.1292	-11.9175	0.0000	-15.6708	-11.2443

Model:	GLM	AIC:	593394401.1164
Link Function:	Log	BIC:	593328509.7837
Dependent Variable:	chemical_value	Log-Likelihood:	-2.9670e+08
Date:	2023-02-13 10:56	LL-Null:	-8.6372e+08
No. Observations:	3815	Deviance:	5.9336e+08
Df Model:	7	Pearson chi2:	1.00e+09
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

Chemical Tanker - Cluster 4	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
distw_log	-0.9473	0.0612	-15.4747	0.0000	-1.0673	-0.8273
pop_o_log	-0.5941	0.0282	-21.0906	0.0000	-0.6493	-0.5389
pop_d_log	0.0538	0.0483	1.1128	0.2658	-0.0409	0.1484
gdp_d_log	0.8439	0.0453	18.6426	0.0000	0.7552	0.9326
gdp_o_log	1.2264	0.0354	34.6065	0.0000	1.1569	1.2959
democracy_o	-0.4845	0.2903	-1.6689	0.0951	-1.0535	0.0845
democracy_d	1.1100	0.2379	4.6664	0.0000	0.6438	1.5762
intercept	-16.2770	0.8686	-18.7392	0.0000	-17.9794	-14.5745

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Model:	GLM	AIC:	24803857709.2829
Link Function:	Log	BIC:	24803353415.2806
Dependent Variable:	container_value	Log-Likelihood:	-1.2402e+10
Date:	2023-02-13 10:56	LL-Null:	-9.5719e+10
No. Observations:	20727	Deviance:	2.4804e+10
Df Model:	7	Pearson chi2:	3.24e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

Containers - Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.9725	0.0133	-73.1787	0.0000	-0.9985	-0.9465
pop_o_log	0.0844	0.0242	3.4886	0.0005	0.0370	0.1319
pop_d_log	0.0503	0.0246	2.0448	0.0409	0.0021	0.0986
gdp_d_log	0.8614	0.0256	33.6997	0.0000	0.8113	0.9115
gdp_o_log	0.7805	0.0263	29.6757	0.0000	0.7289	0.8320
democracy_o	-0.2965	0.3044	-0.9741	0.3300	-0.8931	0.3001
democracy_d	-0.6645	0.2116	-3.1398	0.0017	-1.0793	-0.2497
intercept	-11.9286	0.3305	-36.0901	0.0000	-12.5764	-11.2808

Model:	GLM	AIC:	14712646400.6144
Link Function:	Log	BIC:	14712440447.9244
Dependent Variable:	container_value	Log-Likelihood:	-7.3563e+09
Date:	2023-02-13 10:56	LL-Null:	-4.4875e+10
No. Observations:	9283	Deviance:	1.4713e+10
Df Model:	7	Pearson chi2:	2.49e+10
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

Containers - Cluster 2	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.2907	0.0290	-10.0239	0.0000	-0.3475	-0.2338
pop_o_log	0.3362	0.0362	9.2970	0.0000	0.2653	0.4071
pop_d_log	0.0563	0.0356	1.5798	0.1142	-0.0135	0.1261
gdp_d_log	0.8977	0.0338	26.5294	0.0000	0.8314	0.9641
gdp_o_log	0.6261	0.0325	19.2809	0.0000	0.5625	0.6898
democracy_o	-1.9884	0.1485	-13.3881	0.0000	-2.2795	-1.6973
democracy_d	-0.1652	0.2202	-0.7501	0.4532	-0.5968	0.2664
intercept	-18.5967	0.5192	-35.8207	0.0000	-19.6142	-17.5792

Model:	GLM	AIC:	10434678991.8698
Link Function:	Log	BIC:	10434466905.4551
Dependent Variable:	container_value	Log-Likelihood:	-5.2173e+09
Date:	2023-02-13 10:56	LL-Null:	-2.2204e+10
No. Observations:	9317	Deviance:	1.0435e+10
Df Model:	7	Pearson chi2:	1.71e+10
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

Containers - Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.9515	0.0304	-31.3355	0.0000	-1.0110	-0.8920
pop_o_log	0.0414	0.0437	0.9475	0.3434	-0.0442	0.1270
pop_d_log	-0.1052	0.0293	-3.5849	0.0003	-0.1627	-0.0477
gdp_d_log	0.8395	0.0282	29.7916	0.0000	0.7842	0.8947
gdp_o_log	0.7783	0.0425	18.3108	0.0000	0.6950	0.8616
democracy_o	0.0999	0.2877	0.3473	0.7284	-0.4639	0.6637
democracy_d	0.5029	0.1345	3.7386	0.0002	0.2393	0.7666
intercept	-10.0393	0.5578	-17.9985	0.0000	-11.1326	-8.9461

Model:	GLM	AIC:	5473385357.0025
Link Function:	Log	BIC:	5473302629.7056
Dependent Variable:	container_value	Log-Likelihood:	-2.7367e+09
Date:	2023-02-13 10:56	LL-Null:	-9.9103e+09
No. Observations:	3815	Deviance:	5.4733e+09
Df Model:	7	Pearson chi2:	7.18e+09
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

Containers - Cluster 4	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.2906	0.0405	-31.8297	0.0000	-1.3701	-1.2111
pop_o_log	-0.1932	0.0370	-5.2251	0.0000	-0.2657	-0.1207
pop_d_log	-0.1408	0.0261	-5.3997	0.0000	-0.1919	-0.0897
gdp_d_log	0.6869	0.0300	22.8727	0.0000	0.6281	0.7458
gdp_o_log	1.1232	0.0373	30.1447	0.0000	1.0502	1.1962
democracy_o	-0.6679	0.1732	-3.8553	0.0001	-1.0074	-0.3283
democracy_d	0.0635	0.1786	0.3553	0.7223	-0.2866	0.4135
intercept	-7.6575	0.6856	-11.1689	0.0000	-9.0012	-6.3137

Model:	GLM	AIC:	6505673967.1940
Link Function:	Log	BIC:	6505402577.1036
Dependent Variable:	liquified gas_value	Log-Likelihood:	-3.2528e+09
Date:	2023-02-13 10:56	LL-Null:	-5.8747e+09
No. Observations:	20727	Deviance:	6.5056e+09
Df Model:	7	Pearson chi2:	3.57e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

LNG Carrier - Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.1744	0.0489	-23.9998	0.0000	-1.2703	-1.0785
pop_o_log	-0.6557	0.2302	-2.8487	0.0044	-1.1068	-0.2046
pop_d_log	-0.3443	0.1110	-3.1030	0.0019	-0.5618	-0.1268
gdp_d_log	1.5059	0.1044	14.4193	0.0000	1.3012	1.7106
gdp_o_log	1.1149	0.2143	5.2029	0.0000	0.6949	1.5349
democracy_o	-3.4243	0.8105	-4.2252	0.0000	-5.0128	-1.8359
democracy_d	-4.7192	0.6315	-7.4726	0.0000	-5.9570	-3.4814
intercept	-17.1001	2.2252	-7.6848	0.0000	-21.4614	-12.7388

1

Model:	GLM	AIC:	2594445522.5632
Link Function:	Log	BIC:	2594342984.1562
Dependent Variable:	liquified gas_value	Log-Likelihood:	-1.2972e+09
Date:	2023-02-13 10:56	LL-Null:	-2.3085e+09
No. Observations:	9283	Deviance:	2.5944e+09
Df Model:	7	Pearson chi2:	8.39e+09
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

LNG Carrier - Cluster 2	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.8642	0.0792	-23.5309	0.0000	-2.0194	-1.7089
pop_o_log	-0.7084	0.0547	-12.9558	0.0000	-0.8156	-0.6012
pop_d_log	-0.3540	0.1586	-2.2321	0.0256	-0.6648	-0.0432
gdp_d_log	1.3190	0.2001	6.5920	0.0000	0.9268	1.7111
gdp_o_log	0.5349	0.0679	7.8750	0.0000	0.4018	0.6680
democracy_o	-5.6891	0.4940	-11.5156	0.0000	-6.6574	-4.7208
democracy_d	-4.7913	1.3642	-3.5122	0.0004	-7.4650	-2.1175
intercept	5.0634	1.9057	2.6570	0.0079	1.3283	8.7984

1

Model:	GLM	AIC:	450536318.2426
Link Function:	Log	BIC:	450431902.4188
Dependent Variable:	liquified gas_value	Log-Likelihood:	-2.2527e+08
Date:	2023-02-13 10:56	LL-Null:	-4.3601e+08
No. Observations:	9317	Deviance:	4.5052e+08
Df Model:	7	Pearson chi2:	3.11e+09
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

LNG Carrier - Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.2264	0.0993	-12.3552	0.0000	-1.4210	-1.0319
pop_o_log	1.2666	0.1577	8.0306	0.0000	0.9574	1.5757
pop_d_log	-0.6371	0.1254	-5.0793	0.0000	-0.8830	-0.3913
gdp_d_log	1.5527	0.1745	8.8990	0.0000	1.2107	1.8947
gdp_o_log	-0.2858	0.1466	-1.9487	0.0513	-0.5732	0.0017
democracy_o	1.3958	0.8461	1.6496	0.0990	-0.2626	3.0542
democracy_d	2.2201	0.5020	4.4226	0.0000	1.2362	3.2040
intercept	-13.5476	2.6575	-5.0980	0.0000	-18.7561	-8.3391

Model:	GLM	AIC:	535628258.4719
Link Function:	Log	BIC:	535586067.8792
Dependent Variable:	liquified gas_value	Log-Likelihood:	-2.6781e+08
Date:	2023-02-13 10:56	LL-Null:	-4.0627e+08
No. Observations:	3815	Deviance:	5.3562e+08
Df Model:	7	Pearson chi2:	1.97e+09
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

LNG Carrier - Cluster 4	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.2165	0.0792	-15.3595	0.0000	-1.3718	-1.0613
pop_o_log	-0.6475	0.0466	-13.8852	0.0000	-0.7389	-0.5561
pop_d_log	-0.0295	0.1050	-0.2810	0.7787	-0.2353	0.1763
gdp_d_log	0.7382	0.1168	6.3178	0.0000	0.5092	0.9672
gdp_o_log	0.2871	0.0806	3.5618	0.0004	0.1291	0.4451
democracy_o	-7.3816	0.5299	-13.9293	0.0000	-8.4203	-6.3430
democracy_d	1.8988	0.6094	3.1159	0.0018	0.7044	3.0931
intercept	8.1648	1.8154	4.4974	0.0000	4.6066	11.7230

1

Model:	GLM	AIC:	14716138333.7263
Link Function:	Log	BIC:	14715756015.0076
Dependent Variable:	oil_value	Log-Likelihood:	-7.3581e+09
Date:	2023-02-13 10:56	LL-Null:	-1.7837e+10
No. Observations:	20727	Deviance:	1.4716e+10
Df Model:	7	Pearson chi2:	3.54e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

Oil Tanker- Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-1.1293	0.0291	-38.7767	0.0000	-1.1863	-1.0722
pop_o_log	-0.2175	0.1186	-1.8333	0.0668	-0.4500	0.0150
pop_d_log	0.2558	0.0710	3.6005	0.0003	0.1165	0.3950
gdp_d_log	0.8617	0.0694	12.4147	0.0000	0.7257	0.9978
gdp_o_log	0.9495	0.1119	8.4865	0.0000	0.7302	1.1688
democracy_o	-4.8446	0.4291	-11.2890	0.0000	-5.6857	-4.0035
democracy_d	-0.6807	0.5076	-1.3409	0.1799	-1.6756	0.3142
intercept	-12.0214	1.4128	-8.5088	0.0000	-14.7905	-9.2523

Model:	GLM	AIC:	12599885427.1829
Link Function:	Log	BIC:	12599735190.9873
Dependent Variable:	oil_value	Log-Likelihood:	-6.2999e+09
Date:	2023-02-13 10:56	LL-Null:	-1.2624e+10
No. Observations:	9283	Deviance:	1.2600e+10
Df Model:	7	Pearson chi2:	3.37e+10
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

Oil Tanker- Cluster 2	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.9463	0.0410	-23.0830	0.0000	-1.0266	-0.8659
pop_o_log	-0.8467	0.0391	-21.6537	0.0000	-0.9233	-0.7700
pop_d_log	0.2147	0.0797	2.6955	0.0070	0.0586	0.3708
gdp_d_log	0.6447	0.0745	8.6546	0.0000	0.4987	0.7907
gdp_o_log	0.9810	0.0470	20.8897	0.0000	0.8889	1.0730
democracy_o	-4.8270	0.4472	-10.7933	0.0000	-5.7036	-3.9505
democracy_d	0.6936	0.5597	1.2393	0.2152	-0.4034	1.7905
intercept	-3.9738	0.8393	-4.7347	0.0000	-5.6188	-2.3288

Model:	GLM	AIC:	2527259613.2556
Link Function:	Log	BIC:	2527107382.2158
Dependent Variable:	oil_value	Log-Likelihood:	-1.2636e+09
Date:	2023-02-13 10:56	LL-Null:	-2.2932e+09
No. Observations:	9317	Deviance:	2.5272e+09
Df Model:	7	Pearson chi2:	6.38e+09
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

Oil Tanker- Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.7469	0.0632	-11.8097	0.0000	-0.8709	-0.6229
pop_o_log	0.3807	0.0882	4.3145	0.0000	0.2078	0.5537
pop_d_log	-0.4738	0.0673	-7.0443	0.0000	-0.6056	-0.3420
gdp_d_log	1.2286	0.0657	18.6934	0.0000	1.0998	1.3575
gdp_o_log	0.4277	0.0840	5.0943	0.0000	0.2632	0.5923
democracy_o	-2.6091	0.5174	-5.0426	0.0000	-3.6232	-1.5950
democracy_d	3.7248	0.3734	9.9751	0.0000	2.9929	4.4567
intercept	-13.1849	1.2772	-10.3232	0.0000	-15.6882	-10.6816

Model:	GLM	AIC:	4877577179.4106
Link Function:	Log	BIC:	4877511996.2887
Dependent Variable:	oil_value	Log-Likelihood:	-2.4388e+09
Date:	2023-02-13 10:56	LL-Null:	-4.9572e+09
No. Observations:	3815	Deviance:	4.8775e+09
Df Model:	7	Pearson chi2:	1.03e+10
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

Oil Tanker- Cluster 4	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.5708	0.0701	-8.1418	0.0000	-0.7083	-0.4334
pop_o_log	-0.7233	0.0481	-15.0414	0.0000	-0.8176	-0.6291
pop_d_log	-0.2563	0.0536	-4.7779	0.0000	-0.3614	-0.1511
gdp_d_log	1.0587	0.0593	17.8531	0.0000	0.9425	1.1750
gdp_o_log	0.9048	0.0472	19.1581	0.0000	0.8122	0.9973
democracy_o	-3.1308	0.6185	-5.0621	0.0000	-4.3430	-1.9186
democracy_d	2.3886	0.3257	7.3348	0.0000	1.7503	3.0269
intercept	-10.2629	1.2897	-7.9578	0.0000	-12.7906	-7.7352

Model:	GLM	AIC:	13185469349.7762
Link Function:	Log	BIC:	13185027473.7969
Dependent Variable:	ro-ro_value	Log-Likelihood:	-6.5927e+09
Date:	2023-02-13 10:56	LL-Null:	-3.3005e+10
No. Observations:	20727	Deviance:	1.3185e+10
Df Model:	7	Pearson chi2:	1.88e+10
Df Residuals:	20719	Scale:	1.0000
Method:	IRLS		

Ro-Ro - Cluster 1	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.9434	0.0199	-47.3343	0.0000	-0.9825	-0.9043
pop_o_log	0.1733	0.0456	3.8020	0.0001	0.0840	0.2627
pop_d_log	0.1367	0.0400	3.4209	0.0006	0.0584	0.2150
gdp_d_log	0.9227	0.0423	21.8033	0.0000	0.8397	1.0056
gdp_o_log	0.9173	0.0473	19.4044	0.0000	0.8247	1.0100
democracy_o	-0.8411	0.4032	-2.0861	0.0370	-1.6314	-0.0509
democracy_d	0.1584	0.2579	0.6143	0.5390	-0.3470	0.6639
intercept	-19.8565	0.7240	-27.4259	0.0000	-21.2755	-18.4374

1

Model:	GLM	AIC:	1673231059.5600
Link Function:	Log	BIC:	1673066812.9478
Dependent Variable:	ro-ro_value	Log-Likelihood:	-8.3662e+08
Date:	2023-02-13 10:56	LL-Null:	-2.3448e+09
No. Observations:	9283	Deviance:	1.6732e+09
Df Model:	7	Pearson chi2:	5.36e+09
Df Residuals:	9275	Scale:	1.0000
Method:	IRLS		

Ro-Ro - Cluster 2	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.5778	0.0417	-13.8705	0.0000	-0.6594	-0.4961
pop_o_log	-0.2598	0.0291	-8.9250	0.0000	-0.3169	-0.2028
pop_d_log	0.4310	0.0523	8.2414	0.0000	0.3285	0.5335
gdp_d_log	0.3727	0.0488	7.6312	0.0000	0.2770	0.4684
gdp_o_log	1.1936	0.0394	30.3106	0.0000	1.1164	1.2707
democracy_o	1.5967	0.1802	8.8606	0.0000	1.2435	1.9499
democracy_d	1.0939	0.3024	3.6171	0.0003	0.5012	1.6867
intercept	-17.8835	0.9517	-18.7920	0.0000	-19.7487	-16.0183

1

Model:	GLM	AIC:	2668730337.0768
Link Function:	Log	BIC:	2668549826.4356
Dependent Variable:	ro-ro_value	Log-Likelihood:	-1.3344e+09
Date:	2023-02-13 10:56	LL-Null:	-5.8823e+09
No. Observations:	9317	Deviance:	2.6686e+09
Df Model:	7	Pearson chi2:	4.02e+09
Df Residuals:	9309	Scale:	1.0000
Method:	IRLS		

Ro-Ro - Cluster 3	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.7978	0.0352	-22.6933	0.0000	-0.8668	-0.7289
pop_o_log	0.1419	0.0526	2.6971	0.0070	0.0388	0.2450
pop_d_log	-0.3898	0.0243	-16.0373	0.0000	-0.4375	-0.3422
gdp_d_log	1.0803	0.0322	33.5300	0.0000	1.0172	1.1435
gdp_o_log	0.9116	0.0542	16.8101	0.0000	0.8053	1.0178
democracy_o	1.0049	0.5095	1.9723	0.0486	0.0063	2.0034
democracy_d	0.0060	0.1518	0.0398	0.9683	-0.2914	0.3035
intercept	-19.0708	0.6505	-29.3149	0.0000	-20.3458	-17.7957

Model:	GLM	AIC:	693641903.1353
Link Function:	Log	BIC:	693575646.7974
Dependent Variable:	ro-ro_value	Log-Likelihood:	-3.4682e+08
Date:	2023-02-13 10:56	LL-Null:	-8.9083e+08
No. Observations:	3815	Deviance:	6.9361e+08
Df Model:	7	Pearson chi2:	1.29e+09
Df Residuals:	3807	Scale:	1.0000
Method:	IRLS		

Ro-Ro - Cluster 4	Coef.	Std.Err.	z	P> |z|	[0.025	0.975]
distw_log	-0.8745	0.0436	-20.0497	0.0000	-0.9600	-0.7890
pop_o_log	-0.3038	0.0382	-7.9482	0.0000	-0.3787	-0.2289
pop_d_log	-0.3740	0.0288	-12.9677	0.0000	-0.4306	-0.3175
gdp_d_log	0.6188	0.0338	18.2921	0.0000	0.5525	0.6851
gdp_o_log	1.2473	0.0438	28.4558	0.0000	1.1614	1.3332
democracy_o	0.9736	0.2252	4.3231	0.0000	0.5322	1.4150
democracy_d	1.1663	0.2390	4.8807	0.0000	0.6980	1.6347
intercept	-11.3147	0.9396	-12.0422	0.0000	-13.1562	-9.4731

2. MariTEAM model

Energy demand for shipping is based on the bottom-up MariTEAM model that combines ship technical information, weather hindcast data, and satellite data to calculate energy demand, fuel consumption, and direct ship emissions for several pollutants (CO_2, CH_4, N_2O, NMVOC, SO_2, SO_4, CO, OC, EC, BC) based on the global fuel mix, i.e., heavy fuel oil (HFO), marine gas oil (MGO), and liquefied natural gas (LNG). For more details on the model formulation, see [2]

Ships are modeled individually based on extensive data collection and processing. Ship technical parameters

are organized in a database developed on the basis of the Sea-web Ships database, from which we have included around 50 thousand IMO-registered vessels under operation in the year 2018. Missing ship parameters are filled based on a combination of regression models. The sailing routes are obtained through a collection of terrestrial AIS (Automated Identification System) messages, combined with data obtained by two satellites: NorSat-1 and NorSat-2 launched in 2017 by NSC (Norwegian Space Center) in cooperation with Kystverket (Norwegian Coastal Administration). In this study, ~700 million AIS messages were used after cleaning the data set to remove erroneous data points. Port calls obtained from IHS Markit were included, with data on the date and time of arrival and departure from ports for each vessel. Energy is then estimated by a resistance-based approach to calculate the aerohydrodynamic forces, from which the instantaneous power demand can be derived, using a combination of different methods to calculate calm water, wave, and wind resistance. The total resistance and total propulsive efficiency of the ship are used to compute its brake power and energy demand.

The model performs its calculation individually for each vessel operating in a given year and presents results in a high temporal and spatial resolution. Arrival and departure date from ports (port calls) are then used to distribute energy demand across origin and destination (O&Ds) country pairs that can be ultimately matched with the country-to-country projections in the gravity model. The second step is to aggregate individual ship energy demand in representative ship segments: bulk carriers, chemical tankers, container ships, general cargo ships, oil tankers, LNG carriers, and ro-ro ships. Then, the final energy demand is obtained by the sum of O&D spatial energy demand multiplied by ship segment projections.

3. Narratives of Shared Socioeconomic Pathways

We utilize the Shared Socioeconomic Pathways scenario (SSP)[3] framework for this study to implement a narrative of increasing antagonism in maritime trade. This allows the projections to vary in both geopolitical and socioeconomic futures and creates heterogeneity across country-level trade projections.

For a better understanding of the underlying characteristics of an SSP3 narrative in table S2 we show a comparison across SSP narratives.

Table S2: Comparison of SSP1, SSP2, SSP3, SSP4 and SSP5 by certain categories. Adapted from (O'Neill et al., 2017), Elements that motivate the differentiation of behavioral parameters for maritime demand are highlighted in bold italics

Indicator	SSP1	SSP2	SSP3	SSP4	SSP5
Demographics					
Population growth	Low	Medium	High	High	Low
Migration	Medium	Medium	High	High	High
Economy & Lifestyle					
GDP growth	High	Medium, uneven	Slow	Low in LICs, medium in other countries	High
Inequality	Reduced	Uneven, reduced moderately	High, especially across countries	High, especially within countries	Strongly reduced
Globalization	***Connected markets***	***Semi-open global economy***	***De-globalizing, regional security***	***Globally connected elite***	***Strong***
International Trade	Moderate	Moderate	Strongly constrained	Moderate	High
Consumption	Low material consumption	Material intensive	Material-intensive consumption	Elites: high consumption lifestyles; Rest: low consumption, low mobility	Materialism, Status consumption, High mobility
Diet	***Low meat diets***	***Medium meat consumption***	***N/A***	***N/A***	***Meat-rich diets***
Technology					
Development	Rapid	Medium, uneven	Slow	Rapid in high-tech economies and sectors; slow in other	Rapid

Energy technology change	***Directed away from fossil fuels toward efficiency, renewables***	***Some investment in renewables continued reliance on fossil fuels***	***Slow tech change, directed toward domestic energy sources***	***Diversified investments including efficiency and low-carbon sources***	***Directed toward fossil fuels; alternative sources not actively pursued***
Environment & resources					
Fossil constraints	***Preferences shift away from fossil fuels***	***No reluctance to use unconvention al resources***	***Unconventiona l resources for domestic supply***	***Anticipation of constraints drives up prices with high volatility***	***None***
Land-use	***Strong regulations to avoid environment al trade-offs***	***Medium regulations lead to slow decline in the rate of deforestation***	***Hardly any regulation; continued deforestation due to competition over land and rapid expansion of agriculture***	***Highly regulated in MICs, HICs; largely unmanaged in LICs leading to tropical deforestation***	***Medium regulations lead to slow decline in the rate of deforestatio n***
Agriculture	***Improvemen ts in agriculture productivity; rapid diffusion of best practices***	***Medium pace of tech change in agriculture sector; entry barriers to agriculture markets reduced slowly***	***Low technology development, restricted trade***	***Ag productivity high for large scale industrial farming, low for small-scale farming***	***Highly managed, resource-intensive, rapid increase in productivity***
Policies & instruments					
International cooperation	***Effective***	***Relatively weak***	***Weak, uneven***	***Effective for globally connected economy, not for vulnerable populations***	***Effective for development , limited for environment***
Environmental policy	***Improved management of local and global issues; tighter regulation of pollutants***	***Concern for local pollutants but only moderate success in implementatio n***	***Low priority for environmental issues***	***Focus on local environment in MICs, HICs; little attention to vulnerable areas or global issue***	***Focus on local environment , little concern with global problems***

4. GDP and Population projections

For the historical data on Gross Domestic Product (GDP), we utilize the existing data from the CEEPI gravity dataset[4] which builds upon multiple data sources such as UN Comtrade, European Union, The World Bank, World Trade Organization, and many more.

For the future projections of the growth of trade flows, we utilize data on Gross Domestic Product[3,5] (GDP) and population [3,5] projections and also projections for the understanding of democracy[6,7] (based on the rule of law index) for each of the respective countries. In figure S1 we show the GDP (Figure S1 A)), Population (Figure S1 B)), and GDP per capita (Figure S1 C)) to better understand the underlying dynamics. In this study, we aim to develop a consistent narrative of growing antagonism and thus an SSP3 narrative[8] (see table S2). Thus we only use SSP3 projections in this study.

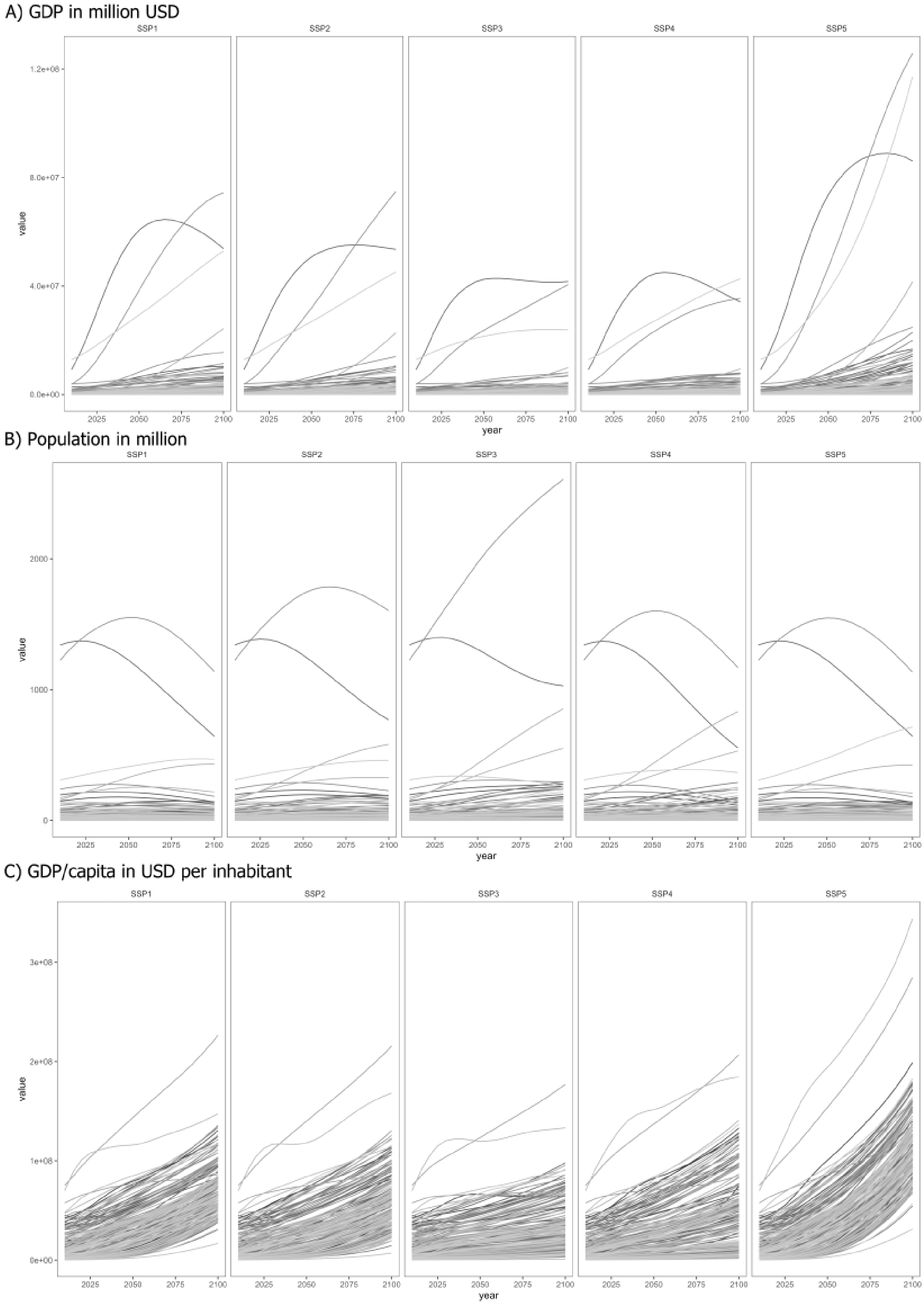


Figure S1: GDP, Population, and GDP per capita for each scenario. For this study, we only used SSP3 projections

5. Democracy historical and future data

To estimate the future impacts of increasing antagonism in maritime trade, we utilize historical data on democracy levels in the form of a democracy index. We use the Varieties of Democracy (V-Dem) liberal democracy index as an underlying index to estimate the regression results shown in table S1[9].

"The liberal principle of democracy emphasizes the importance of protecting individual and minority rights against the tyranny of the state and the tyranny of the majority. The liberal model takes a "negative" view of political power insofar as it judges the quality of democracy by the limits placed on government. This is achieved by constitutionally protected civil liberties, the strict rule of law, an independent judiciary, and effective checks and balances that, together, limit the exercise of executive power. To make this a measure of liberal democracy, the index also takes the level of electoral democracy into account." [9] The democracy index can be between 0 = lowest level of democracy (autocracy) to 1 = highest level of democracy

In Figure S2 we show the historical time series of the liberal democracy index.

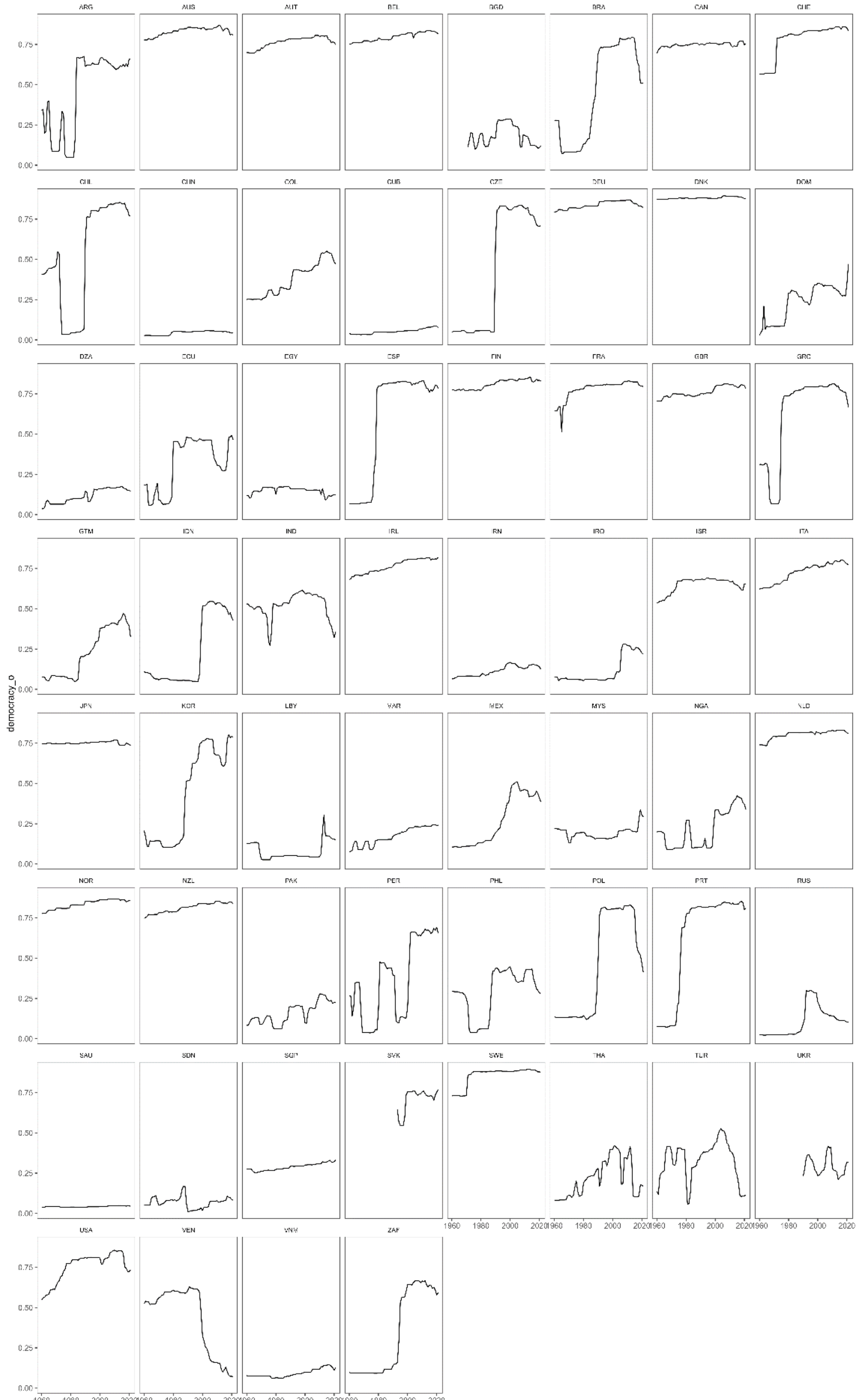


Figure S2: Historical Liberal Democracy index by V-Dem[9] used to estimate historical patterns and coefficients for the gravity model formulation (see table S1)

For the future projections of democracy, we use the rule of law index as a proxy for a democracy index, as there are no projections of any democracy index to our knowledge. The rule of law index answers the questions "To what extent are laws transparently, independently, predictably, impartially, and equally enforced, and to what extent do the actions of government officials comply with the law?" and thus can be used as a proxy for the future understanding of democracy on country level. Further, the rule of laws means "that laws are general, possible to obey, and fairly applied" [10]. However, the rule of law index projections, which are historically also provided by V-Dem, come from Soergel et. al[6,7]. The rule of law index is calculated via a model that incorporates the following key drivers: "(logit-transformed) the rule of law in the previous year, the change of (logit-transformed) the rule of law in the previous year, the GDP per capita growth in the previous year, the interaction between GDP per capita growth and the level of the (logit-transformed) the rule of law in the previous year, the share of men without primary education in the previous year, the gender gap in primary education in the previous year and the population growth in the previous year" [7] The index solution space is between 0 very rule of law valuation to 1 very high rule of law valuation in the respective country. The underlying dynamics on a country level can be seen in figure S3. Comparing figures S2 and S3, one can spot a few differences when it comes to the 2020 values, yet the long-term trend is of importance for future projections.

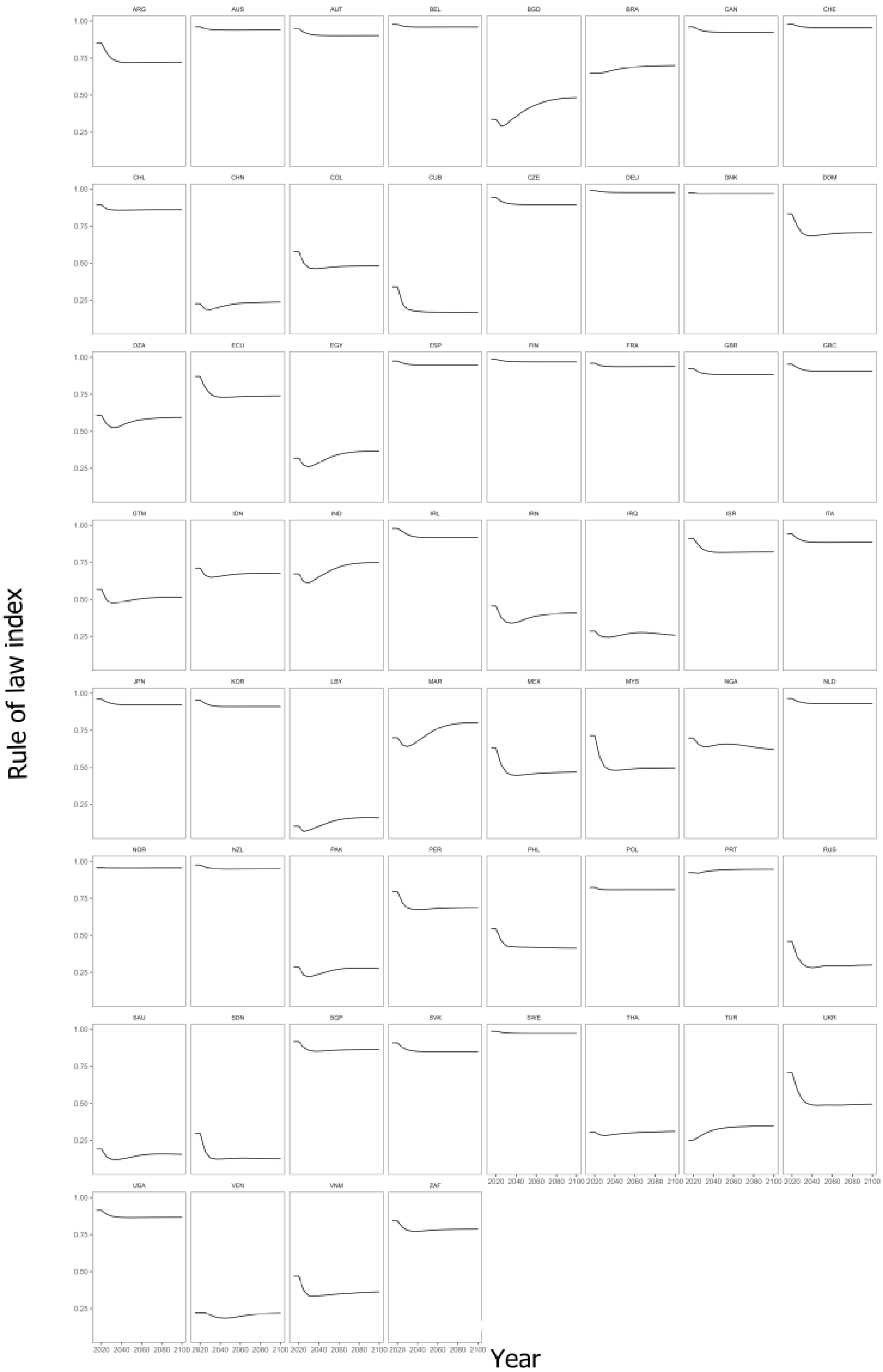


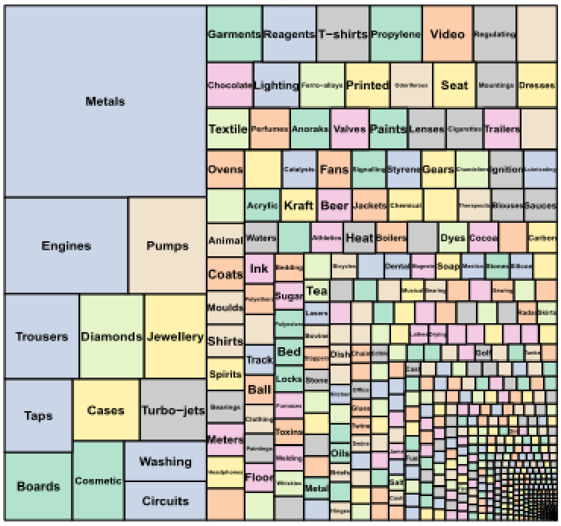
Figure S3: The rule of law projections used as a proxy for future democracy indices.

6. Shipping Segments

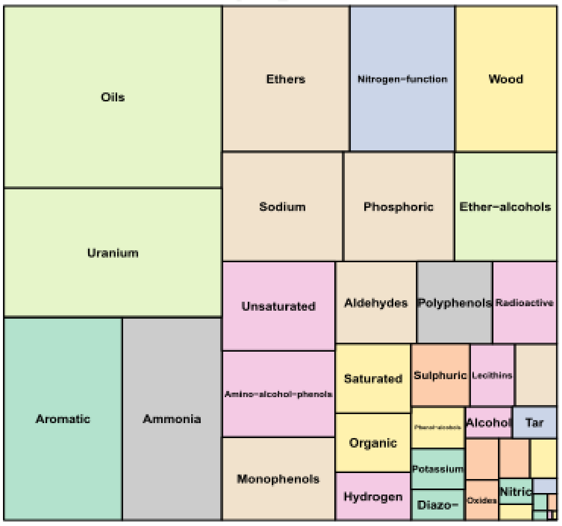
In this study we aggregate over 5000product codes up to 6 shipping segment. For this we use BACI data[11] to parse commodities in specific ship segments by value and weight. This follows the methodology and segment division established by Wang et. al.[12].

In Figure S4 we show what the respective shipping segments consists of relative to their 2020 monetary values per specific product category.

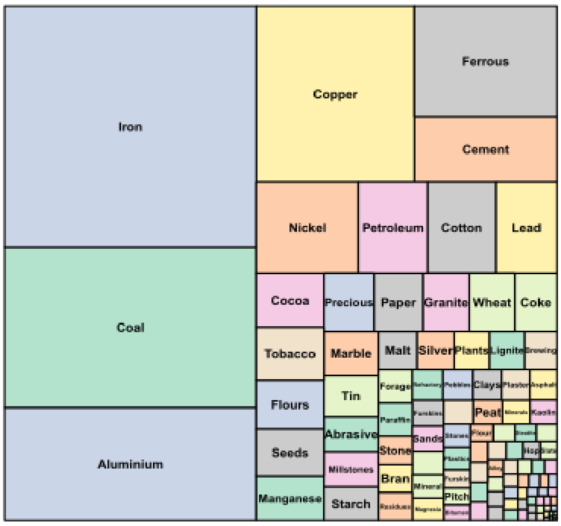
Containers



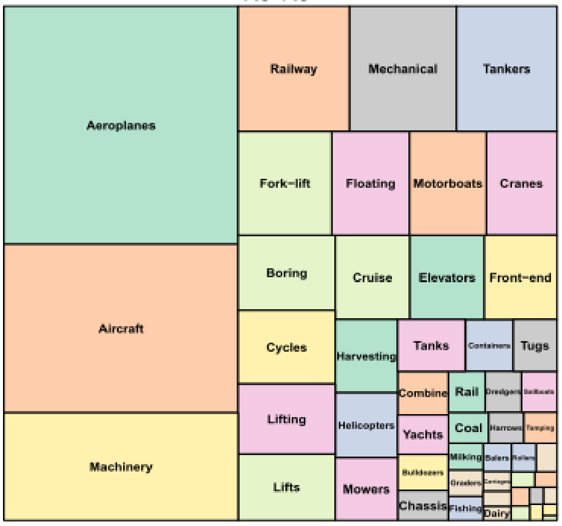
Chemical Tanker



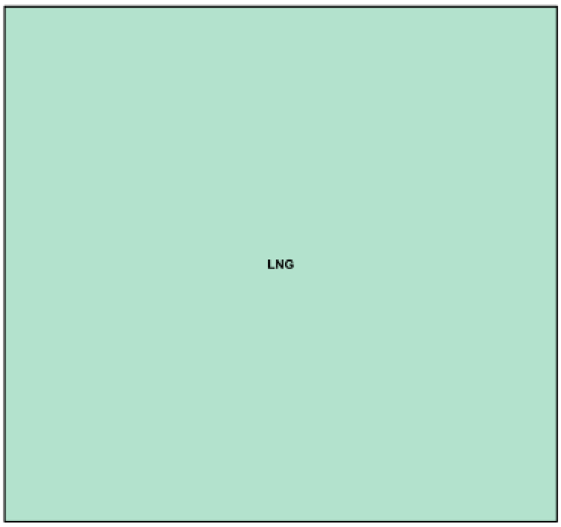
Bulk Carrier



Ro-Ro



LNG Carrier



Oil Tanker

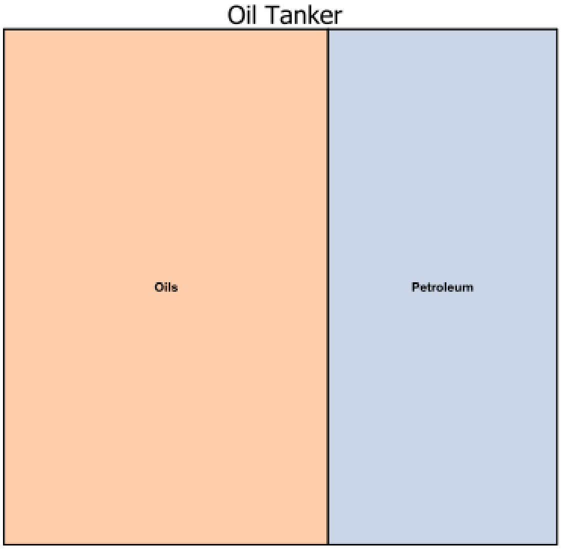


Figure S4: Shipping segments and their underlying product categories based on[11,12]

Further, in figure S5, we show the total monetary values of the respective shipping segments in a pie diagram to understand the different weights per segment compared to the total trade volume in 2020. One can clearly identify that container trade is by far to largest in terms of monetary size compared to the total trade volume in 2020 in USD.

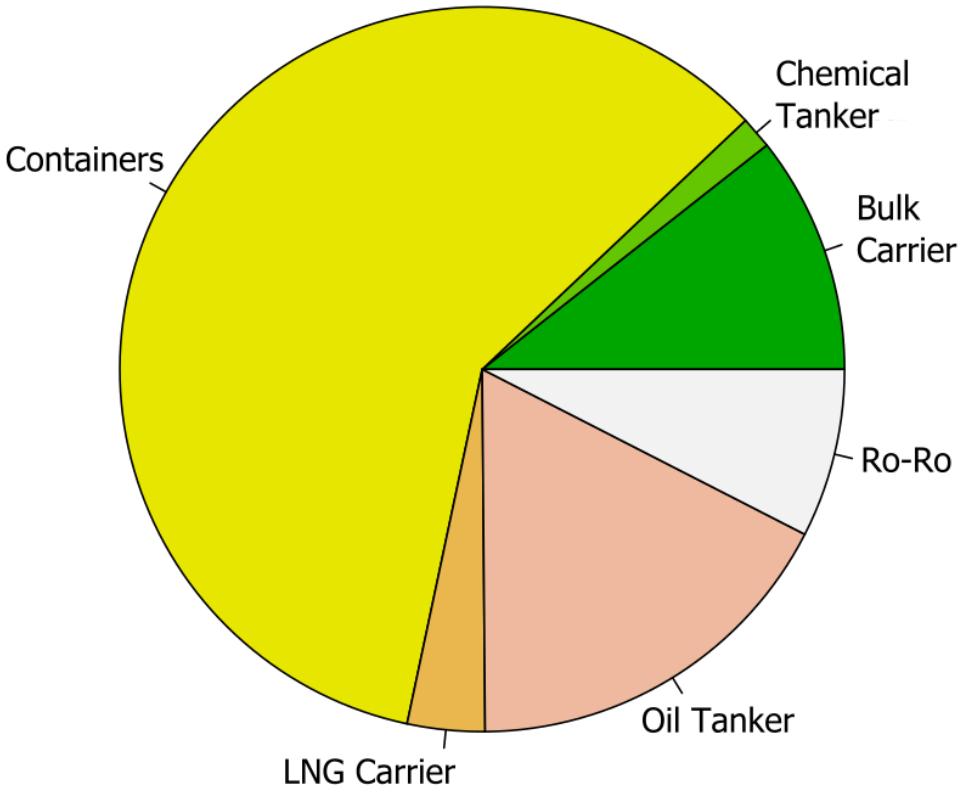


Figure S5: Total bilateral maritime trade volume per ship segment relative to total trade volume.

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