

SUPPLEMENTARY APPENDIX (NOT FOR PUBLICATION)
INTERNATIONAL TRANSMISSION OF INEQUALITY THROUGH TRADE
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Online Data Appendix

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Country and Year Coverage

The empirical analysis relies on different data sets that at maximum cover 158 countries in 1990-2019. The list of countries is as follows:

AGO, ALB, ARE, ARG, ARM, AUS, AUT, AZE, BDI, BEL, BEN, BFA, BGD, BGR, BHS, BIH, BLR, BLZ, BOL, BRA, BRB, BTN, BWA, CAF, CAN, CHE, CHL, CHN, CIV, CMR, COL, COM, CPV, CRI, CYP, CZE, DEU, DJI, DNK, DOM, DZA, ECU, EGY, ESP, EST, ETH, FIN, FJI, FRA, GAB, GBR, GEO, GHA, GIN, GMB, GNB, GRC, GRD, GTM, GUY, HKG, HND, HRV, HTI, HUN, IDN, IND, IRL, IRN, ISL, ISR, ITA, JAM, JOR, JPN, KAZ, KEN, KGZ, KHM, KOR, KWT, LAO, LBN, LBR, LKA, LSO, LTU, LUX, LVA, MAR, MDA, MDG, MDV, MEX, MKD, MLI, MLT, MNE, MNG, MOZ, MRT, MUS, MWI, MYS, NAM, NER, NGA, NIC, NLD, NOR, NPL, NZL, OMN, PAK, PAN, PER, PHL, POL, PRT, PRY, QAT, ROM, RUS, RWA, SAU, SDN, SEN, SGP, SLE, SLV, SRB, SUR, SVK, SVN, SWE, SWZ, SYC, SYR, TGO, THA, TJK, TKM, TTO, TUN, TUR, TWN, TZA, UGA, UKR, URY, USA, UZB, VEN, VNM, YEM, ZAF, ZMB, ZWE

Depending on the data coverage and availability, the sample sizes differ across regressions and rely on subsets of countries and years above. Note that the theoretical mechanism and the empirical tests that I propose do not discriminate across exporter and importer countries.

Figure 1: Panel A & B

Panel A uses data from the [World Inequality Database \(2023\)](#). Panel B uses data from the [World Bank Development Indicators \(2023\)](#).

Figure 3: Panel A, B, C & Table 1

Figure 3 (Panels A, B, and C) and Table 1 are based on the regressions results that rely on the following data:

- Export transaction data are provided by the Trade and Integration Unit of the World Bank Research Department, as part of their efforts to build the [Exporter Dynamics Database \(2022\)](#) described in [Fernandes et al. \(2016\)](#). The raw data requires application for restrictive access. The sources for the data for each country and access application details are available at <http://www.worldbank.org/en/research/brief/exporter-dynamics-database>.
- The data on the Gini coefficients are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).
- The data on population and real per capita GDP are from the [Penn World Tables \(2021\)](#) (version 10.0).

Export transactions data are available for 11 exporter countries (Albania, Burkina Faso, Bulgaria, Guatemala, Jordan, Malawi, Mexico, Peru, Senegal, Uruguay, and Yemen) and 158 importer countries in 1993-2012.

Table 2

Table 2 is based on the regression results that rely on the following data that cover 154 countries in 1997-2017:

- Trade flows are from the [Comtrade Database \(2022\)](#)
- Trade openness is based on total export/import flows from the [Comtrade Database \(2022\)](#) and GDP data from the [World Bank Development Indicators \(2023\)](#) supplemented with UN Stats.
- The data on the Gini coefficients are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).
- The data on population and real per capita GDP are from the [Penn World Tables \(2021\)](#) (version 10.0).

The instrumental variable approach relies on the following data:

- air_{ij} is population-weighted great circle distance between countries i and j from the [CEPII Gravity Database \(2022\)](#) described in [Mayer and Zignago \(2011\)](#).

- sea_{ij} is sea distance between countries i and j from the [CERDI Sea Distance Database \(2016\)](#) described in [Bertoli et al. \(2016\)](#).

Table 3

Table 3 is based on the calibration results that rely on the following data for 40 countries in 2011:

- Average real income, y_i , is per capita real GDP from the [Penn World Tables \(2021\)](#) (version 10.0).
- Gini coefficients, G_i , are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).
- Income shares of the top 1% of population, S_i , are from the [World Inequality Database \(2023\)](#).
- Export/Output share are calculated using data from the [World Input-Output Database \(2016\)](#) described in [Timmer et al. \(2015\)](#).
- Trade shares, λ_{ij} are calculated using data from the [World Input-Output Database \(2016\)](#) described in [Timmer et al. \(2015\)](#).
- Share of exporters, F_{ij} are calculated using the number of exporter firms from the [Trade by Enterprise Characteristics Database \(2020\)](#) provided by the OECD and [Exporter Dynamics Database \(2022\)](#). The total number of firms from the [Industrial Statistics Database \(2020\)](#) (version 2) provided by the United Nations Industrial Development Organization. Note that the number of total firms for Canada are from the [Structural and Demographic Business Statistics \(2022\)](#) (revision 4). To avoid missing data and measurement errors, the data were averaged across three years 2011-2013. Missing ij observations were imputed using $\min_i \{F_{ij}\}$. If calculated $F_{ij} > 1$, they were replaced with $1/J \sum_j F_{ij}$. Observations for the Rest of the World were calculated using exporter- and importer averages.
- Domestic exit rates from the [Structural and Demographic Business Statistics \(2022\)](#) are used to calculate F_{ii} , the data were averaged across three years 2011-2013. Missing F_{ii} data were replaced with the sample average.

Table A1 & Figure A1

Table A1 and Figure A1 are based on the regression results that rely on the following data:

- Trade flows are from the [Comtrade Database \(2022\)](#)
- air_{ij} is population-weighted great circle distance between countries i and j from the [CEPII Gravity Database \(2022\)](#) described in [Mayer and Zignago](#)

(2011).

- sea_{ij} is sea distance between countries i and j from the CERDI Sea Distance Database (2016) described in Bertoli et al. (2016).

Table OA1

Table OA1 is based on the following data:

- Exporter Dynamics Database (2022)

Table OA2

Table OA2 is based on the following data:

- Export revenues are from Exporter Dynamics Database (2022)
- Gini coefficients, G_i , are from the Standardized World Income Inequality Database (2022) (version 9.3) described in Solt (2020).
- Per capita real income and population are from the Penn World Tables (2021) (version 10.0).

Figure OA1

Figure OA1 is based on the following data:

- Export revenues are from Exporter Dynamics Database (2022)
- Gini coefficients, G_i , are from the Standardized World Income Inequality Database (2022) (version 9.3) described in Solt (2020).

Figure OA3

Figure OA3 is based on the following data:

- Export transaction data are provided by the Trade and Integration Unit of the World Bank Research Department, as part of their efforts to build the Exporter Dynamics Database (2022) described in Fernandes et al. (2016). The raw data requires application for restrictive access. The sources for the data for each country and access application details are available at <http://www.worldbank.org/en/research/brief/exporter-dynamics-database>.
- The data on the Gini coefficients are from the Standardized World Income Inequality Database (2022) (version 9.3) described in Solt (2020).
- The data on population and real per capita GDP are from the Penn World Tables (2021) (version 10.0).

Table OA3

Table OA3 is based on the following data:

- The data on standard deviation of export revenues are from the [Exporter Dynamics Database \(2022\)](#).
- The data on the Gini coefficients are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).
- The data on population and real per capita GDP are from the [Penn World Tables \(2021\)](#) (version 10.0).

Table OA4

Table OA4 is based on the following data:

- The data on the number of exporters and average revenues are from the [Exporter Dynamics Database \(2022\)](#).
- The data on the Gini coefficients are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).
- The data on population and real per capita GDP are from the [Penn World Tables \(2021\)](#) (version 10.0).

Figure OA4

Figure OA4 is based on the following data:

- Trade flows are from the [Comtrade Database \(2022\)](#)
- The data on the Gini coefficients are from the [Standardized World Income Inequality Database \(2022\)](#) (version 9.3) described in [Solt \(2020\)](#).

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Online Appendix A: Additional Estimation Details and Results

In this appendix, I provide details of the data used in Section 2.1. The data come from the *Exporter Dynamics Database* described in Fernandes et al. (2016). This is a restricted-access data set but one can apply for access using the form available at <http://www.worldbank.org/en/research/brief/exporter-dynamics-database>. Export transactions data are available for 11 countries (Albania, Burkina Faso, Bulgaria, Guatemala, Jordan, Malawi, Mexico, Peru, Senegal, Uruguay, and Yemen) in 1993-2012. I provide descriptive statistics in terms of coverage by exporter country in Table OA1.

Table OA1: COVERAGE IN EXPORTER DYNAMICS DATABASE

exporter	observations	# export markets	# firms	years
ALB	25,602	176	6,074	2004-2012
BFA	4,763	138	995	2005-2010
BGR	193,371	211	48,899	2001-2006
GTM	72,518	184	11,198	2003-2010
JOR	40,987	187	4,986	2003-2010
MEX	660,302	224	134,409	2000-2009
MWI	4,175	141	1,690	2004-2009
PER	169,545	216	25,910	1993-2009
SEN	21,664	146	2,244	2000-2010
URY	43,532	189	6,449	2001-2012
YEM	3,471	131	896	2008-2012

Notes: The table reports the data coverage in terms of total observations, number of import markets, number of exporter firms and years. *Data Sources:* Exporter Dynamics Database.

I provide summary statistics for the variables used in estimating RIF regressions in Equation (1) in Table OA2.

Table OA2: SUMMARY STATISTICS (EXPORTER DYNAMICS DATABASE)

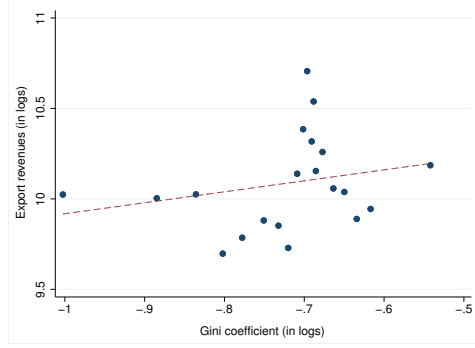
Statistics	Export Revenues (log)	Gini (log)	Real GDP (log)	Population (log)
Mean	10.78	-0.73	9.71	3.24
Std. Dev.	2.66	0.11	0.96	1.58
p10	7.60	-0.87	8.32	1.44
p25	9.10	-0.78	8.99	2.03
p50	10.74	-0.71	9.67	3.20
p75	12.46	-0.66	10.60	4.17
p90	14.13	-0.63	10.84	5.67

Notes: The table reports summary statistics for the variables used in RIF estimation in Equation (1).

Data Sources: Exporter Dynamics Database, Penn World Tables, Standardized World Income Inequality Database.

To demonstrate the variation in key variables, I also produce and report a bin-scatter plot of (log) export revenues vs. (log) Gini coefficients in Figure OA1.

The relationship is positive with an estimated coefficient of 0.606 and standard error of 0.025.



Notes: The figure plots binscatter of (log) export revenues versus (log) Gini coefficients. Data Sources: Exporter Dynamics Database, Standardized World Income Inequality Database.

Figure OA1: BINSCTTER PLOT

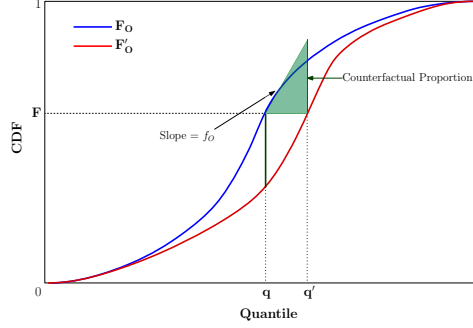
Next, I provide additional details on estimation in Section 2.1, where I use RIF-OLS estimator developed in Firpo et al. (2009). This estimator allows to calculate unconditional quantile effects and has been used in many different settings. For example, Dube (2019) uses RIF-OLS to study the effects of the minimum wage across the income distribution, whereas Gray et al. (2023) estimate the effects of work requirements on earnings distribution.

Here I provide further details behind this estimator. As before let O denote (log) export revenues of firm ϕ from country i in year t to any destination market and let F_O denote its cumulative distribution function observed in the data. Further, let F'_O denote its counterfactual distribution that would occur if there were small changes in, e.g., inequality in one of the export markets. Recall that $\mathbf{q}_\kappa$ denotes κ -quantile of the unconditional distribution of O . The unconditional quantile partial effect can then be calculated as follows:

$$\mathbf{q}'_\kappa - \mathbf{q}_\kappa = F'^{-1}_O(\kappa) - F^{-1}_O(\kappa).$$

The approach in Firpo et al. (2009) allows to calculate the unconditional quantile partial effect by inverting the counterfactual distribution $F'_O(\kappa)$ using a local linear approximation. The approach offers significant computational advantages relative to the global inversion alternative. The local linear approximation works as follows. Given the value of $F_O(\kappa)$, one can calculate the corresponding quantile $\mathbf{q}_\kappa$ and proportion as $F_O(\mathbf{q}_\kappa) - F'_O(\mathbf{q}_\kappa)$. Once the proportion is calculated, one

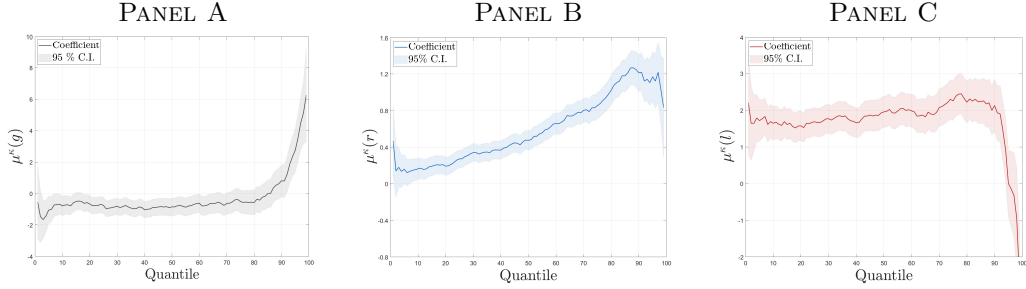
can use f_O as the slope and approximate the counterfactual quantile as in Figure OA2. The unconditional quantile partial effect can then be approximated as: $(F'_O(\kappa) - F_O(\kappa))/f_O(\kappa)$.



Notes: The figure illustrates estimation of the unconditional quantile partial effect using RIF-OLS estimator.

Figure OA2: COUNTERFACTUAL QUANTILES

The main specification that uses RIF regression in the main text in equation (1) includes firm-exporter-importer and firm-year fixed effects. The results, however, are robust to using an alternative source of variation. I re-run the panel model in equation (1) with firm-exporter-importer and exporter-year fixed effects and report the results in Figure OA3.



Notes: The figure reports the results of the RIF-OLS regression that includes firm-exporter-importer and exporter-year fixed effects. Standard errors are clustered at the firm-exporter-importer level.

Data Sources: Exporter Dynamics Database, Penn World Tables, Standardized World Income Inequality Database.

Figure OA3: QUANTILE RIF-OLS REGRESSION RESULTS (ROBUSTNESS)

The results in Figure OA3 suggest that the RIF results are robust to using alternative econometric specifications.

Next, I provide the details behind the regressions in Section 2.2. Recall that I

run the following gravity regression to generate instruments for export inequality exposure:

$$\ln(X_{ij,t}) = \mu_t^{sea} \log(sea_{ij}) + \mu_t^{air} \log(air_{ij}) + \mathbf{exp}_{i,t} + \mathbf{imp}_{j,t} + \mathbf{pair}_{ij} + e_{ij,t}.$$

I report the estimated coefficients in Table OA3.

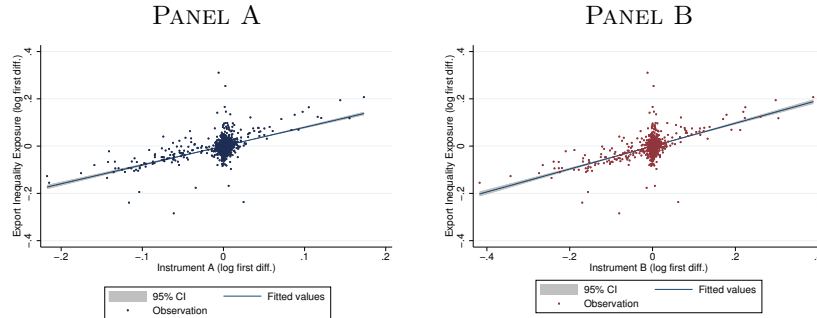
Table OA3: TIME-VARYING GRAVITY COEFFICIENTS

	coef.	s.e.		coef.	s.e.		coef.	s.e.		coef.	s.e.
μ_2^{air}	-0.007	0.026	μ_{12}^{air}	-0.199	0.035	μ_2^{sea}	0.017	0.018	μ_{12}^{sea}	0.003	0.025
μ_3^{air}	-0.009	0.028	μ_{13}^{air}	-0.178	0.035	μ_3^{sea}	0.013	0.019	μ_{13}^{sea}	0.001	0.026
μ_4^{air}	-0.092	0.031	μ_{14}^{air}	-0.189	0.035	μ_4^{sea}	0.000	0.020	μ_{14}^{sea}	-0.004	0.025
μ_5^{air}	-0.124	0.032	μ_{15}^{air}	-0.180	0.036	μ_5^{sea}	0.031	0.024	μ_{15}^{sea}	-0.020	0.026
μ_6^{air}	-0.102	0.032	μ_{16}^{air}	-0.134	0.037	μ_6^{sea}	0.018	0.022	μ_{16}^{sea}	-0.021	0.027
μ_7^{air}	-0.141	0.033	μ_{17}^{air}	-0.137	0.037	μ_7^{sea}	0.015	0.023	μ_{17}^{sea}	-0.043	0.026
μ_8^{air}	-0.174	0.034	μ_{19}^{air}	-0.136	0.037	μ_8^{sea}	0.013	0.024	μ_{19}^{sea}	-0.037	0.026
μ_9^{air}	-0.161	0.036	μ_{20}^{air}	-0.108	0.037	μ_9^{sea}	0.008	0.026	μ_{20}^{sea}	-0.024	0.026
μ_{10}^{air}	-0.173	0.035	μ_{12}^{air}	-0.096	0.036	μ_{10}^{sea}	0.021	0.025	μ_{12}^{sea}	-0.032	0.025
μ_{11}^{air}	-0.225	0.036	μ_{21}^{air}	-0.067	0.036	μ_{11}^{sea}	0.022	0.027	μ_{21}^{sea}	-0.039	0.025

Notes: The gravity regression is based on the data that cover 31,350 country pairs in 1997-2017 and include exporter-year-specific, importer-year-specific, and pair-specific fixed effects. Standard errors are clustered by country pairs.

Data Sources: Comtrade Database, CEPII Database, CERDI Database.

Instruments A and B are generated using these coefficients in Table OA3 and subsequently used to generate the results in Table 2 in the main text. I plot these two instruments against the measure of $T_{i,t}$ in first differences in Figure OA4, which confirms that the instruments are valid and sufficiently strong.



Notes: The figure reports the results of the first-stage regressions of the instrumental variable approach in first differences. Panel A reports the results for Instrument A. Panel B reports the results for Instrument B.

Data Sources: Comtrade Database, CEPII Database, CERDI Database.

Figure OA4: IV FIRST-STAGE RESULTS

Next, I provide additional support of **R1** using an expanded version of the *Exporter Dynamics Database*. While customs-level data are available for a limited

number of origin countries described in [Fernandes et al. \(2016\)](#), the coverage improves significantly in terms of the standard deviation of exporter revenues across firms within each exporter-importer-year combination. The respective dataset covers the period from 1997 to 2014. It includes 65 exporter countries, and 248 importer countries in manufacturing. For each year and country pair, it reports the number of exporter firms and the “standard deviation of export values”. Exporters are defined as firms “that always export a total of more than \$1,000 in any year.” I test the relationship in **R1** by estimating the following panel model:

$$SD_{ij,t} = \xi(g) \ln(G_{j,t}) + \xi(r) \ln(R_{j,t}) + \xi(l) \ln(L_{j,t}) + Z_{ij,t}^{\xi} \Gamma^{\xi} + \epsilon_{ij,t}, \quad (\text{OA1})$$

where $Z_{ij,t}^{\xi}$ is a vector of controls, which includes *it*-exporter-year fixed effects and *ij*-pair fixed effects. The resulting dataset is an unbalanced panel including 8,163 country pairs and covering 18 years. The regression in Equation (OA3) is subject to several potential concerns about the estimation of $\xi(g)$. As [di Giovanni et al. \(2018\)](#) point out, countries that are similar to each other may experience common shocks, e.g., to technology, that would increase the standard deviation of profits in countries that have similar export patterns. However, the regression model that I employ relies on within-exporter-importer-pair variation across time conditional on exporter-year fixed effects that take out variation in all *i, t*-specific shocks and control for shocks that may be common across exporters. I also include pair fixed effects that control for the fact that countries may have similar export patterns. These fixed effects also capture unobservable bilateral-time-invariant characteristics such as geographic distance and other natural trade barriers. In the end, $\xi(g)$ reflects how changes in the importer-country inequality affect changes in the dispersion of *bilateral* export profits conditional on all exporter-year and bilateral shocks.

The results are reported in Panel A of Table [OA4](#). The coefficient on (log) Gini coefficient of the importer country is positive and precisely estimated. The results suggest that, conditional on time-invariant bilateral trade barriers and exporter-year-specific shocks, higher income inequality in import markets is associated with higher profit dispersion across exporter firms. This lends additional support to **R1**.

Table OA4: DISPERSION OF EXPORT REVENUES AND EXPORT MARKET INEQUALITY

	DEPENDENT VARIABLES: $SD_{ij,t}$ AND $SD_{ij,s,t}$			
	PANEL A		PANEL B	
	coef.	s.e.	coef.	s.e.
$\ln(G_{j,t})$	0.82	(0.22)	0.23	(0.06)
$\ln(R_{j,t})$	0.07	(0.03)	0.05	(0.01)
$\ln(L_{j,t})$	-0.21	(0.06)	-0.11	(0.02)
Observations	49,746		654,396	

Table notes: In both panels, the regressions use data from 1997 to 2014. In Panel A, the regressions are based on 8,163 country pairs and include pair- and exporter-year-fixed effects. Standard errors are clustered at the country-pair level. In Panel B, the regressions are based on 7,775 country pairs $\times$ 78 HS-2 sectors and include pair-sector and exporter-year-sector-fixed effects. Standard errors are clustered at the country-pair-sector level. Standard deviation of SD is normalized to unity.

Data Sources: Exporter Dynamics Database, Penn World Tables, Standardized World Income Inequality Database.

I further check the robustness of the results by looking at the effects of consumer income inequality on the dispersion of export profits within more narrowly defined sectors. This empirical design controls for the possibility that there are unobserved sectoral shocks that are common across exporter-importer-year triples that are driving the sign of $\xi(g)$. I consider *HS* two-digit sectors and run the following panel-data model:

$$SD_{ij,s,t} = \xi_s(g) \ln(G_{j,t}) + \xi_s(r) \ln(R_{j,t}) + \xi_s(l) \ln(L_{j,t}) + Z_{ij,s,t}^\xi \Gamma_s^\xi + \epsilon_{ij,s,t}, \quad (\text{OA2})$$

where subscript s denotes sectors and $Z_{ij,s,t}^\xi$ is a vector of controls that now includes *ist*-exporter-sector-year and *ijs*-pair-sector fixed effects. Hence, I use the variation in the dispersion of export profits for a given pair of countries within *HS* two-digit-level sectors across time conditional on controlling for exporter-sector-year-specific shocks. As Panel B of Table OA4 reports, the coefficient $\xi_s(g)$ is consistent with the previous results, positive and precisely estimated, which lends additional support to **R1**.

I also confirm the relationship in **R1** using an expanded version of the *Exporter Dynamics Database*. While customs-level data are available for a limited number of origin countries described in [Fernandes et al. \(2016\)](#), the coverage improves significantly in terms of the standard deviation of exporter revenues across firms

within each exporter-importer-year combination. The respective dataset covers the period from 1997 to 2014. It includes 65 exporter countries, and 248 importer countries in manufacturing. For each year and country pair, it reports the number of exporter firms and the “standard deviation of export values”. Exporters are defined as firms “that always export a total of more than \$1,000 in any year.” I test the relationship in **R1** by estimating the following panel model:

$$SD_{ij,t} = \xi(g) \ln(G_{j,t}) + \xi(r) \ln(R_{j,t}) + \xi(l) \ln(L_{j,t}) + Z_{ij,t}^{\xi} \Gamma^{\xi} + \epsilon_{ij,t}, \quad (\text{OA3})$$

where $Z_{ij,t}^{\xi}$ is a vector of controls, which includes *it*-exporter-year fixed effects and *ij*-pair fixed effects. The resulting dataset is an unbalanced panel including 8,163 country pairs and covering 18 years.

In Section 3, I specify consumer targeting costs as fixed costs. Here, I provide empirical evidence in support of this assumption. For that, I return to the data in the *Exporter Dynamics Database* used in Table OA4. I run the following panel models:

$$\ln(N_{ij,t}) = \zeta(g) \ln(G_{j,t}) + \zeta(r) \ln(R_{j,t}) + \zeta(l) \ln(L_{j,t}) + Z_{ij,t}^{\zeta} \Gamma^{\zeta} + \epsilon_{ij,t}, \quad (\text{OA4})$$

$$\ln(A_{ij,t}) = \varrho(g) \ln(G_{j,t}) + \varrho(r) \ln(R_{j,t}) + \varrho(l) \ln(L_{j,t}) + Z_{ij,t}^{\varrho} \Gamma^{\varrho} + \epsilon_{ij,t}, \quad (\text{OA5})$$

where $N_{ij,t}$ is the number of exporters from *i* to *j* in year *t*; $A_{ij,t}$ are average revenues; $Z_{ij,t}$ ’s are vectors of controls, which include *it*-exporter-year fixed effects and *ij*-pair fixed effects. I report the results of the regressions in (OA4) and (OA5) in Panel A and B of Table OA5, respectively.

Table OA5: EXPORTERS, REVENUES AND EXPORT MARKET INEQUALITY

	DEPENDENT VARIABLES: $N_{ij,t}$ AND $A_{ij,t}$			
	PANEL A		PANEL B	
	coef.	s.e.	coef.	s.e.
$\ln(G_{j,t})$	-0.49	(0.17)	-0.36	(0.32)
$\ln(R_{j,t})$	0.39	(0.03)	0.22	(0.05)
$\ln(L_{j,t})$	0.06	(0.07)	0.27	(0.14)
Observations	57,407		49,746	

Table notes: The regressions use data from 1997 to 2014. The regressions include pair- and exporter-year-fixed effects. Standard errors are clustered at the country-pair level.

Data Sources: Exporter Dynamics Database, Penn World Tables, Standardized World Income Inequality Database.

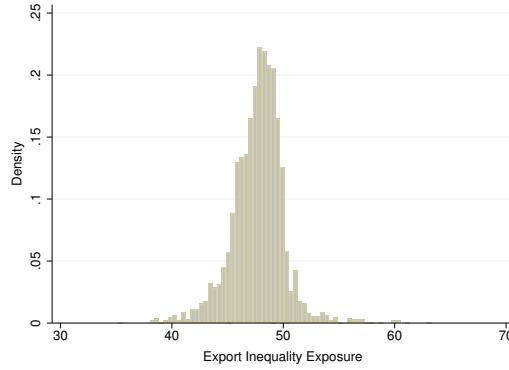
The results in Table OA5 suggest that conditional on the average level of income and total population in the importing country, higher income inequality

negatively affects the number of exporters from i to j . The effects on average revenues is not significantly different from zero. This lends support to the fixed-cost specification of the consumer targeting costs.

Next, I provide details on the export inequality exposure measure $T_{i,t}$ calculated in Equation (2) as follows:

$$T_{i,t} = \sum_{j \neq i} T_{ij,t} G_{j,t}.$$

Note that since $\sum_{j \neq i} T_{ij,t} = 1$, $T_{i,t}$ is simply a weighted average of the Gini coefficient faced by exporter j across all partner countries j . Hence, $T_{i,t}$ is measured in the same units as Gini coefficients.



*Notes: The figure illustrates estimation of the unconditional quantile partial effect.
Data Sources: Comtrade Database, Standardized World Income Inequality Database.*

Figure OA5: DENSITY OF EXPORT INEQUALITY EXPOSURE $T_{ij,t}$

Online Appendix B: Additional Model and Calibration details

In this appendix, I provide additional derivation and simulation details behind the results in Section 3.1. Recall that the profit of firm ϕ is as follows:

$$\pi(z(\phi); \phi) = \frac{L}{\sigma} \left(\frac{\sigma}{\sigma-1} \frac{w}{\phi} \right)^{1-\sigma} \int_{\varphi} s \left(x(z(\phi), f(\varphi); \delta) \right) y(\varphi) P(\varphi)^{\sigma-1} h(\varphi) d\varphi - \kappa(z(\phi)).$$

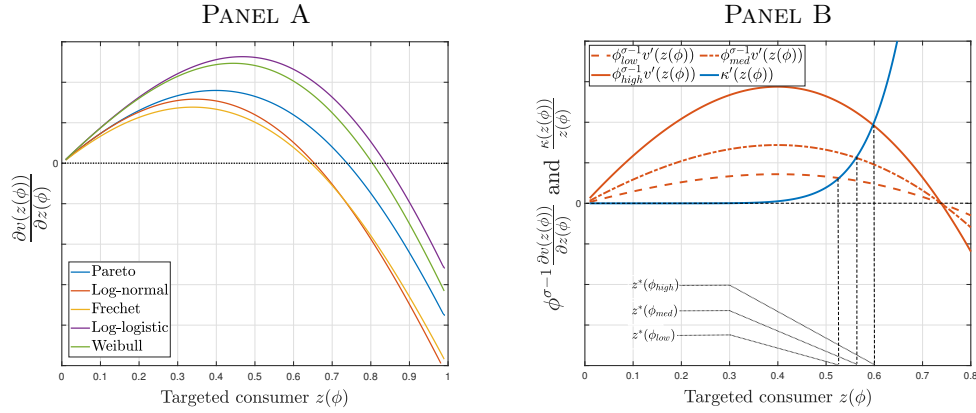
First, pinning down the optimal $z^*(\phi)$ requires differentiating the profit function with respect to $z(\phi)$. For brevity and without loss of generality, let me normalize non-firm-specific variables as $\frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} w \right)^{1-\sigma} L = 1$. Then the optimality condition for $z(\phi)$ for the interior solution can be specified as:

$$\phi^{\sigma-1} \frac{\partial v(z(\phi))}{\partial z(\phi)} = \frac{\partial \kappa(z(\phi))}{\partial z(\phi)} \text{ where } v(z(\phi)) = \int_{\varphi} s\left(x(z(\phi), f(\varphi))\right) y(\varphi) P(\varphi)^{\sigma-1} h(\varphi) d\varphi \quad (\text{OB1})$$

I study the optimality condition in Equation (OB1) in two steps. First, I look at the derivative of $v(z(\phi))$ when income distributions are fat-tailed including:

- Pareto, Log-normal, Fréchet, Log-Logistic, and Weibull
- The distributions are disciplined to the same first two moments

Providing analytical results would require multiple implausible simplifications of the model; instead, I provide the results based on simulations and numerical analysis. Five distributions cover an overwhelming majority of approaches used to model income distributions. The results are robust to using mixtures as in Nigai (2017) as well as other right-skewed distributions.



Notes: Panel A illustrates the derivative of $v(z(\phi))$ with respect to $z(\phi)$ when income is distributed according to Pareto, Log-normal, Fréchet, Log-logistic, and Weibull. Panel B illustrates the selection of optimal $z^*(\phi)$ for low, medium, and high values of productivity ϕ .

Figure OB1: OPTIMAL CONSUMER TARGETING

Panel A of Figure OB1 illustrates $\frac{\partial v(z(\phi))}{\partial z(\phi)}$ under five different shapes of income distribution. In all cases, the derivative is a strictly concave function. The intuition behind this shape is as follows: when $h(\varphi)$ is right skewed, firms face a trade-off between the size of consumer segment that they can capture and the average income level in that segment. Initially, $\frac{\partial v(z(\phi))}{\partial z(\phi)}$ grows as the income effect dominates and firms have incentives to target consumers farther on the $f(\varphi)$ line. However, as firms target consumers in the right tail their segment size

shrinks such that eventually $\frac{\partial v(z(\phi))}{\partial z(\phi)}$ declines and hits zero at the maximum value of $v(z(\phi))$. This pattern emerges in all simulations for all plausible shapes of the income distribution.

The optimal value of $z(\phi)$ will be lower than the one that corresponds to maximum $v(z(\phi))$ at $\frac{\partial v(z(\phi))}{\partial z(\phi)} = 0$ due to the targeting costs $\kappa(\phi)$. Given that the derivative of $v(z(\phi))$ is concave, more productive firms will target richer consumers if the derivative of $\kappa(z(\phi))$ is strictly convex.

The choice of optimal $z^*(\phi)$ is depicted in Panel B of Figure [OB1](#) where I keep the income distribution as Pareto and consider three firms with productivity levels $\phi_{low} < \phi_{med} < \phi_{high}$. I plot the left-hand side of the optimality condition in Equation [\(OB1\)](#), $\phi^{\sigma-1} \frac{\partial v(z(\phi))}{\partial z(\phi)}$, for these three values of ϕ that intersect the derivative of the targeting-cost function at optimal $z^*(\phi)$'s.

The results in Figure [OB1](#) illustrate a positive assortative matching between firms and consumers. This leads to result (i) in the main text of Section [3.1](#) that states that more productive firms choose to target consumer segments with higher incomes such that the optimal $z^*(\phi)$ is increasing in ϕ .

Next, I examine the implications of the positive assortative matching between firms and consumers by looking at how profits vary across firms to generate results (ii) and (iii) in the main text of Section [3.1](#). The results are presented in Figure [5](#) in the main text. To produce the results in the figure, I need to parameterize economic primitives in the profit function. I parameterize the productivity and income distributions to Pareto with scale parameter $b = 0.5$ and shape parameters $\theta = 3.5$. Labor endowments are set to $L = 10$, $\alpha = 3$, $m = 2$, and $\sigma = 4$. The remaining parameters and variables are set to unity.

Next, I provide further details behind calibration of parameter δ . It is chosen to match $\xi = 0.23$ estimated in Table [OA4](#). Since $i = \text{Mexico}$ and $j = \text{USA}$, I drop subscripts. I also normalize w_i and τ_{ij} to unity. Then the following system is solved in to calibrate ϕ 's in two steps. In the first step, I calculate optimal $z^*(\phi)$:

$$\begin{aligned} (1.i) \quad v(z(\phi)) &= \int_{\varphi} \left(1 + \delta(z(\phi) - f(\varphi))^2\right)^{-1} y(\varphi) dF(y(\varphi)) \\ (1.ii) \quad v(0) &= \int_{\varphi} (1 + \delta f(\varphi)^2)^{-1} y(\varphi) dF(y(\varphi)) \end{aligned}$$

$$\begin{aligned}
(1.iii) \quad \pi(\phi, z(\phi)) &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \phi^{\sigma-1} Lv(z(\phi)) - \kappa - mz(\phi)^\alpha \\
(1.iv) \quad z^*(\phi) &= \arg \max_{z(\phi)} \left\{ \pi(\phi, z(\phi)) \right\}
\end{aligned}$$

In the second step, conditional $z^*(\phi)$, I calculate

$$\begin{aligned}
(2.i) \quad v(z^*(\phi)) &= \int_{\varphi} \left(1 + \delta (z^*(\phi) - f(\varphi))^2 \right)^{-1} y(\varphi) dF(y(\varphi)) \\
(2.ii) \quad \phi^* &= \left(\frac{\sigma}{\sigma-1} \right) \left(\frac{\sigma \kappa (m^{\frac{1}{\alpha}} + z^*(\phi))^\alpha}{Lv(z^*(\phi))} \right)^{\frac{1}{\sigma-1}} \\
(2.iii) \quad \kappa &= (\phi^*)^{\sigma-1} \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} \left(\frac{Lv(z^*(\phi))}{\sigma (m^{\frac{1}{\alpha}} + z^*(\phi))^\alpha} \right) \\
(2.iv) \quad \phi &= r(\phi, z(\phi))^{\frac{1}{\sigma-1}} \left(\frac{\sigma}{\sigma-1} \right) \left(Lv(z^*(\phi)) \right)^{\frac{1}{1-\sigma}}
\end{aligned}$$

Given counterfactual changes in the income distribution and repeating steps (1.i)-(1.iv), counterfactual revenues can then be calculated as:

$$\begin{aligned}
(3.i) \quad v(z^*(\phi)) &= \int_{\varphi} \left(1 + \delta (z^*(\phi) - f(\varphi))^2 \right)^{-1} y(\varphi) dF(y(\varphi)) \\
(3.ii) \quad \phi^* &= \left(\frac{\sigma}{\sigma-1} \right) \left(\frac{\sigma \kappa (m^{\frac{1}{\alpha}} + z^*(\phi))^\alpha}{Lv(z^*(\phi))} \right)^{\frac{1}{\sigma-1}} \\
(3.iii) \quad r(\phi, z(\phi)) &= \phi^{\sigma-1} \left(\frac{\sigma}{\sigma-1} \right)^{1-\sigma} Lv(z^*(\phi))
\end{aligned}$$

Next I can calculate model analogue of ξ as:

$$\xi'(\delta') = \frac{SD' - SD}{\ln(G') - \ln(G)},$$

where SD' is counterfactual standard deviation of Mexican exporter-firms' revenues and G' is the counterfactual change in the United States Gini coefficient (by construction the Gini coefficient goes up by 1% relative to the benchmark level).

Online Appendix C: Model Solution Details

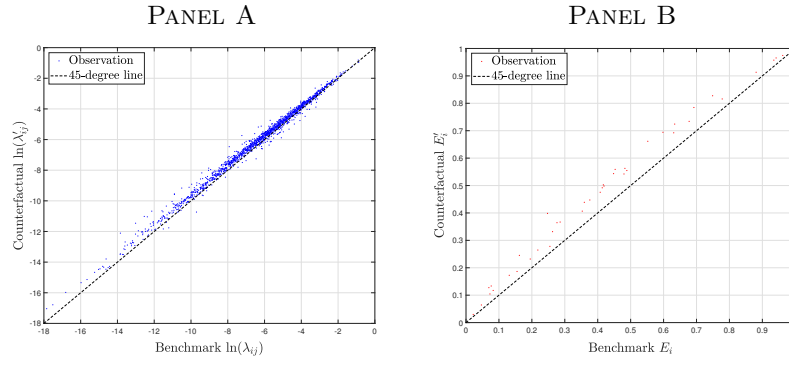
The solution algorithm proceeds in several steps. I approximate $H_j(\phi)$ and ϕ as vectors of 1000×1 size. This means that there are $10^6 \cdot J \cdot J$ potential

firm-to-consumer segment linkages. Given other primitives of J economies, the equilibrium satisfies equations in (i) – (xv). The solution algorithm relies on the contraction mapping routine that looks for a fixed point.

$$\begin{aligned}
(i) \quad v_j(z_{ij}(\phi)) &= \int_{\varphi} \left(1 + \delta(z_{ij}(\phi) - f_j(\varphi))^2\right)^{-1} P_j(\varphi)^{\sigma-1} y_j(\varphi) dH_j(\varphi) \\
(ii) \quad v_i(0) &= \int_{\varphi} (1 + \delta f_i(\varphi)^2)^{-1} P_i(\varphi)^{\sigma-1} y_i(\varphi) dH_i(\varphi) \\
(iii) \quad \pi_{ij}(\phi, z_{ij}(\phi)) &= \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \frac{w_i \tau_{ij}}{\phi} \right)^{1-\sigma} L_j v_{ij}(\phi, z_{ij}(\phi)) - w_i \kappa_{ij} \left(m^{\frac{1}{\alpha}} + z_{ij}(\phi) \right)^{\alpha} . \\
(iv) \quad z_{ij}^*(\phi) &= \arg \max_{z_{ij}(\phi)} \left\{ \pi_{ij}(\phi, z_{ij}(\phi)) \right\} \\
(v) \quad \phi_{ij}^* &= \left(\frac{\sigma}{\sigma-1} w_i \tau_{ij} \right) \left(\frac{m \sigma w_i \kappa_{ij}}{L_j v_j(\phi, 0)} \right)^{\frac{1}{\sigma-1}} \\
(vi) \quad \pi_{ij}(\phi_{ij}^*, z_{ij}^*(\phi)) &= \begin{cases} 0 & \text{for } \phi \leq \phi_{ij}^* \\ \frac{1}{\sigma} \left(\frac{\sigma}{\sigma-1} \frac{w_i \tau_{ij}}{\phi} \right)^{1-\sigma} L_j v_{ij}(\phi, z_{ij}^*(\phi)) - w_i \kappa_{ij} \left(m^{\frac{1}{\alpha}} + z_{ij}(\phi) \right)^{\alpha} & \text{for } \phi > \phi_{ij}^* \end{cases} \\
(vii) \quad \Pi_i(\phi) &= \sum_j \mathbf{1}_{\phi \geq \phi_{ij}^*} \pi_{ij}(\phi, z_{ij}^*(\phi)) \\
(viii) \quad y_i(\varphi) &= \begin{cases} \ell_i(\phi) w_i & \text{for } \phi \leq \phi_i^* \\ \ell_i(\phi) w_i + \Pi_i(\phi) & \text{for } \phi > \phi_i^* \end{cases} \\
(ix) \quad N_i &= L_i (1 - H_i(\phi_i^*)) \\
(x) \quad d_i &= \frac{N_i}{L_i} \int_{\phi_i^*} \Pi_i(\phi) dH_i(\phi) \text{ where } \phi_i^* = \min_j \{\phi_{ij}^*\} \\
(xi) \quad y_i &= w_i + d_i \\
(xii) \quad P_j(\varphi) &= \left(\sum_k N_k \left(\frac{\sigma}{\sigma-1} w_k \tau_{kj} \right)^{1-\sigma} \int_{\phi_{kj}^*} \left(1 + \delta(z_{kj}^*(\phi) - f_j(\varphi))^2\right)^{-1} \phi^{\sigma-1} dH_k(\phi) \right)^{\frac{1}{1-\sigma}} \\
(xiii) \quad X_{ij} &= N_i \left(\frac{\sigma}{\sigma-1} w_i \tau_{ij} \right)^{1-\sigma} L_j \int_{\varphi} \left[\int_{\phi_{ij}^*} \frac{P_j(\varphi)^{\sigma-1} y_j(\varphi)}{(1 + \delta(z_{ij}^*(\phi) - f_j(\varphi))^2)} \phi^{\sigma-1} dH_i(\phi) \right] dH_j(\varphi) \\
(xiv) \quad \lambda_{ij} &= X_{ij} / \sum_i X_{ij} \\
(xv) \quad w_i &= \frac{1}{L_i} \left(\sum_j \lambda_{ij} L_j y_j - D_i \right)
\end{aligned}$$

Online Appendix D: Counterfactual experiments

Figure OD1 reports how trade shares and export-to-output ratio change across country pairs and countries when $\delta'_{ij} = 0$ for all $i \neq j$.



Notes: Panel A illustrates benchmark and counterfactual trade shares in the first counterfactual experiment. Panel B illustrates benchmark and counterfactual export-to-output ratios.

Figure OD1: COUNTERFACTUAL EXPERIMENT (I)