Online Appendix:
The Environmental Bias of Trade Policy

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A Data Details

A.1 Concordances

The paper uses several concordances across definitions and years of industry and product codes. As a general guide, raw data on traded goods, tariffs, and NTBs are at the level of a 6-digit harmonized system (HS) code. Raw U.S. data are at the level of a 6-digit North American Industry Classification System (NAICS) code. Exiobase uses industry codes based on the International Standard Industrial Classification, version 3.1. WIOD also uses its own industry codes. I use published concordances between these various industry codes. I use weighted concordance files when possible, i.e., which express the share of an industry's output in one classification which corresponds to each possible industry in a different classification. Ultimately, I concord raw data to the industry definition of the relevant analysis (Exiobase, U.S., or WIOD).

Concording Exiobase files are fairly straightforward. Exiobase industries were constructed to closely reflect ISIC industries, so I construct a concordance by matching names between these two industry classifications.

Linking U.S. industry codes is more complicated. A few concordances link 2007 NAICS codes to other industry codes. Some of the U.S. political economy explanations are from the May 2007 Current Population Survey, which defines industries using 2007 U.S. census codes (i.e., the codes defined for use in the 2007 U.S. Economic Census, which is distinct from the decennial population census; these codes differ from NAICS codes). I use Census Bureau files to link these census industries to 2007 NAICS industries.[1] The unionization coverage data I use as one political economy explanation use industry codes from the 2000 U.S. census, so I use the same concordance file to link these to 2007 NAICS codes. One sensitivity analysis aggregates the U.S. data to 21 ISIC industries; I link NAICS to ISIC codes using a Census concordance.[2]

Another set of concordances links U.S. industry codes for other years. The 2006 MECS data are at the level of 2002 NAICS codes, so I also link these to ISIC codes using U.S. Census Bureau files.[3] U.S. input-output tables use an input-output industry classification which is similar but not identical to NAICS. I use a file that is part of the 2007 input-output table which contains a concordance between 2007 input-output codes and 2012 NAICS codes. I concord 2012 NAICS codes to 2007 NAICS codes using a concordance file from the U.S. Census Bureau which includes industry shares (file EC1200CBDG1). The PAC contributions data are at the level of 1987 Standard Industrial Classifications (SIC); I link these to NAICS codes using a concordance from the NBER-CES Manufacturing Industry database (Becker et al. 2013). A few datasets report NAICS codes for some observations at 2, 3, 4, or 5 digits; for these more aggregated values, I construct concordances at this more aggregated level and then translate industry codes appropriately.

[1]Downloaded from https://www.census.gov/people/io/files/IndustryCrosswalk90-00-02-07-12.xls, visited 8/18/2017.

[2]Downloaded from https://www.census.gov/eos/www/naics/concordances/concordances.html, visited 8/8/2017.

[3]Downloaded from https://www.census.gov/eos/www/naics/concordances/concordances.html, visited 8/8/2017.

A.2 Global Input-Output Data

I use Exiobase (specifically, version 2.2.2, industry-by-industry, fixed product sales assumption) because it distinguishes 48 countries and 163 industries, about 50 of which are in manufacturing. Five of the "countries" are actually aggregates that include all countries in a given region that are not separately identified in the data, such as the aggregate, "Rest of Asia." Exiobase is supported by the European Union. Other global multi-region input-output tables, like the World Input-Output Database (WIOD), typically distinguish only 20-60 industries, only 15-20 of which are tradable manufacturing industries.

Much of the global value chain literature uses the World Input Output Database (WIOD) and related multi-region input-output tables. I focus on Exiobase, which I believe has not been used in this literature, since it has far richer industry detail than WIOD and related datasets. Exiobase is widely used in industrial ecology research (e.g., Tukker et al. 2013; Moran and Wood 2014; Wood et al. 2015). I report some sensitivity analyses using WIOD (Timmer et al. 2015).

Exiobase is built from several primary data sources (Wood et al. 2015). Exiobase combines supply and use output tables for the EU27 via Eurostat, and for 16 other countries that together cover over 90 percent of global GDP. It measures trade using BACI, which is based on the UN's Comtrade database, and using the UN's services trade databases. To harmonize data across countries, Exiobase also uses data from FAO and the European AgroSAM, the IEA, and other data sources. National fossil fuel use comes from IEA sources, while some industry detail comes from Pulles et al. (2007).

Like all global multi-region input-output tables, Exiobase applies statistical algorithms to harmonize these different datasets. National input-output tables also do this; Horowitz and Planting (2006) describe the process. The final data must satisfy many accounting identities; for example, imports must equal exports, subject to trade imbalances; industry-specific values must add up to national values; the value of intermediate goods plus value added must equal gross output; etc. Harmonization also expresses all countries in the same industries and using the same price concepts.

How does Exiobase compare to other multi-region input-output tables? Several studies compare Exiobase to WIOD and Eora. These studies find that the numbers in these databases are not especially sensitive to the different algorithms used to construct these tables (Geschke et al. 2014), that consumption-based CO_2 accounts (sometimes called a country's "carbon footprint") or raw materials that each country consumes generally differ by less than 10-15 percent across these databases (Moran and Wood 2014; Giljum et al. 2019), and that disaggregation to more industry detail, which is Exiobase's focus, tends to produce more accurate analysis of CO_2 (Steen-Olsen et al. 2014; de Koning et al. 2015). The Global Trade and Analysis Project (GTAP), which constructs another multi-region input-output table, is widely used in computable general equilibrium (CGE) analyses in part since it incorporates a ready-made CGE model, simplified coding language, online support services, and hundreds of parameters. GTAP, however, also includes only around 20 manufacturing industries, and its data construction are less well documented than some other input-output tables. WIOD is generally seen as having higher data quality, which may be because it has fewer countries (43 in WIOD versus 190 in Eora), which lets WIOD rely on data from higher-quality statistics agencies and require less imputation for the additional countries.

Exiobase covers 43 countries plus five rest-of-world aggregates, which is similar to WIOD. The possibility of measurement error in these data is one reason why I report results from three separate input-output tables – Exiobase, WIOD, and U.S. national data – and also obtain completely independent measures of CO_2 emissions for use as an instrumental variable in the U.S. data.

Comparing the U.S. and Exiobase data is complicated by the fact that U.S. NAICS industry codes and Exiobase industry codes do not easily concord to each other and require applying multiple many-to-many concordances. To provide such a comparison while limiting additional measurement error, I select the 30 Exiobase manufacturing industries that have a one-to-one or one-to-many mapping to 4- or 6-digit NAICS codes (thus excluding those with many-to-many links). For these 30 Exiobase industries, I then calculate the mean total emissions rate from the U.S. data (weighting across 6-digit U.S. NAICS industries within an Exiobase industry by the value of shipments). In logs, a regression of the U.S. CO_2 rate calculated from Exiobase data on this rate calculated from U.S. data gets a regression coefficient of 1.035 (robust standard error 0.020), with an R-squared of 0.989. In levels, this regression coefficient is 0.801 (0.210), with an R-squared of 0.56. These are strong correlations, though for a focused sample; since Exiobase is constructed from national input-output tables it is perhaps unsurprising that its patterns for the U.S. are similar to those of the national U.S. input-output table.

I calculate gross output in Exiobase 2.2 (which does not directly report it) as follows. Gross output Y equals the sum of intermediate inputs I and factor payments L, where factor payments are defined to include payments to labor, payments to capital including profits (i.e., including markups), and taxes:

$$Y = I + L \tag{1}$$

To measure intermediate inputs I in millions of Euros for each country×industry, I take the sum across rows (within each column) of the Exiobase Use table. To measure factor payments per gross output L/Y, I use the Exiobase Factor Inputs table and exclude entries recording employment in hours per million Euros or in workers per million Euros. I then calculate L/Y as the sum across rows (within each column) of this table. Finally, simple manipulation of (1) shows that gross output for each country×industry is

$$Y = \frac{I}{1 - \frac{L}{Y}}$$

where I and L/Y are calculated from the Use table and Factor Inputs table as described above.

Given this measure of gross output, I follow Antràs et al. (2012) and Antràs and Chor (2018) in calculating upstreamness. In the raw Exiobase input-output table, each row is an origin country×sector and each column is a destination country×sector. Each entry in this table is in terms of Euros of inputs per Euro of output (i.e., the table is in coefficient form). I convert this to Euros by multiplying each entry by the gross output of the destination country×sector. I calculate total international exports X_{ij} from domestic industry i to foreign buyers of industry j as the sum of this table across columns (within a row), excluding columns with the same origin and destination country. I calculate total international imports

M_{ij} from foreign industry i to domestic industry j as the sum of this table across rows (within a column) which have the same origin and destination country.

The main results use CO_2 emissions from fossil fuel combustion, which is the best-measured and accounts for most greenhouse gas emissions. I also report results using other greenhouse gas emissions. I incorporate two corrections for outliers in the raw data. First, for each greenhouse gas separately, I replace emissions from nitrogen fertilizer production with emissions from phosphorus fertilizer emissions from the same country. Second, for the crude oil extraction industry, I replace non-combustion methane emissions with combustion methane emissions. In both cases, raw data from Exiobase are outliers and exceed estimates from other sources. For similar reasons, in regressions including non-manufacturing goods, I exclude one mining industry with outlier values of emissions rates, "Extraction, liquefaction, and regasification of other petroleum and gaseous materials," which is distinct from crude oil or natural gas extraction.

The quantitative model requires data on CO_2 emissions from production of each fossil fuel in each country. I obtain these data from reports using the International Energy Agency containing data from the year 2007 (IEA 2009b,a), which list the physical units of each fossil fuel produced in each country. I convert these into CO_2 using standard conversion rates of physical units of fossil fuel (i.e., tons or terajoules) to metric tons of CO_2 from the U.S. Energy Information Agency.

In the sensitivity analysis using WIOD, I measure environmental outcomes using data on total CO_2 emissions. I replace the roughly 5 percent of WIOD country$\times$industry observations which have missing CO_2 values to instead have the mean global CO_2 emissions rate for that industry, multiplied by the country$\times$industry's reported gross output. If a country$\times$industry reports zero output, I set CO_2 emissions for that country$\times$industry also to equal zero. To aid computation, I replace the roughly 2 percent of country$\times$industry observations that report zero output to have output 10^{-7}. Because WIOD does not separately distinguish types of mining, in the WIOD estimates all mining activities are combined into one sector, and both electricity generation and transportation are combined into the "other industries" sector. A few WIOD international flows are negative, primarily representing gross fixed capital formation and changes in inventories and valuables. In WIOD estimates that aggregate over industry categories or countries and use trade values as weights in this aggregation, I assume these negative flows instead have values of zero. As with Exiobase, I exclude the five countries missing NTB data (Bulgaria, Cyprus, Malta, Slovak Republic, and Taiwan).

A.3 Political Economy Variables

I group the political economy variables into those reflecting the demand for versus supply of protection. The global data come from Exiobiase, but the U.S.-specific data with greater industry detail come from a range of sources. Optimal tariffs are perhaps the simplest. I use estimates of the export supply elasticity for the U.S. at the 10 digit harmonized system code level from Soderbery (2015); the results are qualitatively similar using estimates from Broda and Weinstein (2006).

A few variables reflect demand for low protection from customers. Industries may lobby for low protection on goods they use as inputs. Industries with a large share of intra-industry trade, i.e., where both exports and imports are common, may have less trade protection since importers lobby for protection while exporters (who are concerned with retaliation) lobby against protection. I measure intra-industry trade using the common measure $1 - \frac{|x_i - m_i|}{x_i + m_i}$, where x_i and m_i represent total exports and imports in industry i (Krugman 1981). These data come from the Census Bureau's Imports and Exports of Merchandise data series.

Another set of political economy variables reflects an industry's demand for protection on its own goods. Declining or "sunset" industries may obtain more government support since sunk costs prevent entry and incentivize incumbents to lobby to protect remaining rents. I calculate the change in the value of shipments for each industry between the years 1977 and 2007, adjusted by industry-specific output deflators, using data from the NBER-CES Manufacturing Industry Database. Industries more exposed to foreign trade have more to gain from protection. I measure the import penetration ratio as log of the total imports divided by the value of shipments, in levels for the year 2007 and as a trend over the period 2002-2007, using data from the NBER-CES database for gross output and Imports of Merchandise for imports. Industries with more workers have more stakeholders potentially benefiting from protection; I calculate each industry's labor share as total workers divided by the value of shipments, using data from the NBER-CES database. Industries with a large share of low skill or low wage workers may obtain protection as a tool for redistribution, either out of general concern for equity or as an alternative to other transfers. I measure mean wages and the share of workers with some college education, using data from the May 2007 Current Population Survey Annual Social and Economic Supplement (CPS-ASEC).[4]

One additional variable measures the "local" air pollution for each industry. I combine the six major air pollutants that the Clean Air Act targets and that are typically measured: carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter smaller than 2.5 micrometers ($PM_{2.5}$), particulate matter smaller than 10 micrometers (PM_{10}), sulfur dioxide (SO_2), and volatile organic compounds (VOC). I measure emissions of each pollutant from the year 2008 data of the National Emissions Inventory (NEI), a national dataset created by the Environmental Protection Agency that measures the tons of pollution emitted from each plant or other source. The costs of these emissions vary over space and across pollutants. To provide a scalar measure of these costs, I use a measure of the marginal damage for each pollutant in each U.S. county, from Muller and Mendelsohn (2012). These damages reflect leading estimates of how air pollution affects health, agriculture, amenities, etc. For each industry, I calculate the damage rate as emissions per industry$\times$pollutant$\times$county times damages per pollutant$\times$county, summed across counties and pollutants, and divided by the industry's revenues.

A separate set of variables reflects the cost of organizing an industry to lobby for protection, i.e., the supply of protection. A challenge in lobbying is overcoming the free-riding problem within each industry to pay for the costs of lobbying (Olson 1965). Concentrated industries or industries with a few larger firms can better overcome the challenge. I measure

[4] A worker's industry is defined from her current job for employed workers, or the most recent job for workers who are unemployed or not in the labor force. I measure the share of workers with at least some college education. For wages, I measure the hourly wage for the Outgoing Rotation Group if it is reported. Otherwise I calculate hourly wages as total wage and salary income for the previous calendar year, divided by the product of weeks worked last year and usual hours worked per week last year. I calculate wages using the individual (earnings) survey weights, and calculate education using the standard individual survey weights.

industry concentration as the share of an industry's output accounted for by the four largest firms, using data from the Economic Census (specifically, the Census of Manufacturers). I calculate mean firm size as the total value of shipments for the industry divided by the total number of establishments in the industry, also using data from the Economic Census. Using the same data, I calculate the standard deviation of firm size (Bombardini 2008). Since capital intensity tends to increase concentration, and is also a primary determinant of comparative advantage and U.S. imports, I also measure the capital share as the value of the capital stock divided by gross output, using the NBER-CES database. High transport costs and geographic dispersion make an industry less geographically or economically concentrated, so more difficult to organize. I measure shipping costs per dollar×kilometer, using data from the U.S. Imports of Merchandise series and CEPII's measure of geographic distance between countries. I measure geographic dispersion as entropy across states, using data from County Business Patterns.[5] Disadvantaged industries, including those with a high share of workers who are unemployed, may have greater incentive to lobby since their opportunity cost of doing so is lower. I measure unemployment rates of workers where industry is defined according to the current or most recent industry worked, using data from the May 2007 CPS. Unions provide an organized association to lobby for protection, so I measure unionization rates using processed values from the May 2007 CPS (Hirsch and MacPherson 2003). I also use one direct though incomplete measure of lobbying on contributions to Political Action Committees (PACs), using data from the Center for Responsive Politics.

Upstreamness turns out to be the most relevant of these variables. Formally, for a closed economy with S industries, upstreamness is $U = [I - d_{ij}Y_j/Y_i]^{-1}\mathbf{1}$. Here, U is an $S \times 1$ column vector where each entry is the upstreamness value for one industry, I is the $S \times S$ identity matrix, d_{ij} is the input-output coefficient (i.e., the dollars of sector i goods needed to produce a dollar of industry j goods), Y_i is the output of industry i, and $\mathbf{1}$ is a vector of ones. The term $d_{ij}Y_j/Y_i$ represents an $S \times S$ matrix where each entry equals the share of output from industry i that industry j purchases. Antràs et al. (2012) show that this measure, originally from Fally (2012), is analytically equivalent to the upstreamness measure described in Antràs and Chor (2013). Versions of these definitions for global multi-region input-output tables are similar, though each observation is an industry×country rather than just an industry (Antràs and Chor 2018).

For the U.S. data, I measure upstreamness using the 2007 U.S. input-output table after redefinitions. Appendix Figure 1, Panel D, plots upstreamness separately for all global production and for U.S. production. In all these graphs, the most upstream industries are on the left and the most downstream industries are on the right. The full measure of upstreamness in Panel D ranges from 5 (most upstream) to 1 (most downstream)

[5] Formally, the analysis defines geographic dispersion as $\sum_j y_{ij} ln y_{ij}$, where $y_{ij} \equiv Y_{ij}/Y_i$, and where Y_{ij} is output of state j and Y_i is total output. In County Business Patterns, each observation lists total employment in a given state×industry. Some values are suppressed due to confidentiality, but identified as falling in one of twelve employment size bins (1 to 19; 20 to 99; etc.). I impute these values as the midpoint of each bin, and impute the top bin (>100,000) as 125,000.

A.4 Trade Policy

Most of the trade policy data are straightforward. The NTB values exclude five countries that are in Exiobase but that I hence exclude from much of the analysis: Bulgaria, Cyprus, Malta, Slovakia, and Taiwan. In cases where tariff data are missing for Luxembourg, I replace them with tariffs for Belgium. The country-by-country map in Figure 5 shows values for many individual countries that are part of regional aggregates like "Rest of Europe" or "Rest of Asia"

The NTB data have some limitations. Unlike tariffs, they are the result of calculations and are not raw data. At the same time, they are widely used in research on trade policy (Irwin 2010; Limão and Tovar 2011; Novy 2013; Handley 2014); Bagwell and Staiger (2011, p. 1250) describe them as "the best [NTB] measures that are available." These data differ by importer and 6-digit HS code, though not by importer-exporter pair.

The time coverage of the NTB data precedes recent policy changes. Between 2009 and 2016, temporary trade barriers including antidumping policies, countervailing duties, and safeguards increased on high income economies' intermediate goods imports from China. These patterns have been less pronounced for final goods trade with China, trade with other countries, or emerging economies (Bown 2018). The U.S. has also increased tariffs in its 2018-2019 trade war on a wide range of goods—initially on intermediate goods, though eventually covering much trade with China. I report some results analyzing these recent changes in tariffs.

One sensitivity analysis compares cooperative and non-cooperative tariffs for the U.S., China, and Japan. The U.S. applies non-cooperative tariffs to Cuba and North Korea. China applies non-cooperative tariffs to Andorra, the Bahamas, Bermuda, Bhutan, the British Virgin Islands, the British Cayman Islands, French Guiana, Palestinian Territory (West Bank and Gaza), Gibraltar, Monserrat, Nauru, Aruba, New Caledonia, Norfolk Island, Palau, Timor-Leste, San Marino, the Seychelles, Western Sahara, and Turks and Caicos Islands. Japanese non-cooperative tariffs apply to Andorra, Equatorial Guinea, Eritrea, Lebanon, North Korea, and Timor-Leste (Ossa 2014).

Appendix Figure 1, Panel A, plots the density of tariffs, excluding the top 1% for visual clarity. The mean global tariff is three to five percent, while the 99th percentile globally is sixty percent. U.S. import tariffs are lower, with mean and median around two percent and the 99th percentile at nearly fifteen percent. Appendix Figure 1, Panel B, plots the density of NTBs. For all global trade, tariffs and NTBs have somewhat similar values; for U.S. imports, average NTBs exceed average tariffs.

A.5 Emissions

Most emissions data are described in the main text. All tons in this paper refer to metric tons. All discussion of CO_2 refers to CO_2 from fossil fuel combustion, which is best measured and accounts for a large majority of CO_2 emissions, except one sensitivity analysis that includes CO_2 from process emissions and other greenhouse gases.

CO_2 accounts for roughly 76 percent of global greenhouse gas emissions, methane (CH_4) accounts for 16 percent, nitrous oxide (N_2O) for 6 percent, and fluorinated gases like hydrofluorocarbons (HFCs) for 2 percent (IPCC 2014). CO_2 accounts for 82 percent of U.S.

greenhouse gas emissions (USEPA 2019). Methane is emitted from extraction, transportation, and processing of coal, oil, and natural gas, in addition to coming from agriculture and landfills. Researchers have a general consensus on the magnitude of CO_2 emissions, but are still debating and improving measurement of methane emissions, particularly from fossil fuels (e.g., Alvarez et al. 2018).

For analyses of the U.S. only, the paper uses four other CO_2 datasets. One is the U.S. detailed benchmark input-output table after redefinitions for 2007, produced by the Bureau of Economic Analysis. For this purpose, I use the industry-by-industry total requirements table. The second data source is the U.S. Manufacturing Energy Consumption Survey (MECS), which reports physical quantities of fossil fuels combusted for a large sample of manufacturing plants in the year 2006. (MECS is only conducted every few years.) The third dataset is the Census of Manufactures (CM), which reports expenditure on electricity and on total fossil fuels for each 6-digit NAICS industry in the year 2007. Because MECS is a sample of only 10,000 plants, I use MECS to measure each industry's tons of CO_2 emissions per dollar of fossil fuel expenditure, and multiply this by the CM data on each industry's total fossil fuel expenditure. The fourth is U.S. emissions coefficients reporting mean national tons of CO_2 emitted per dollar of coal, oil, and natural gas input, obtained from the U.S. Energy Information Agency and Environmental Protection Agency.

For the analysis of the U.S. input-output table, I measure price per BTU produced of each fossil fuel (coal, crude oil, and natural gas) from the Energy Information Agency's year 2016 Annual Energy Review, and I measure metric tons of CO_2 per BTU using EPA emissions factors.[6] Analysis of the U.S. data excludes observations with missing emissions or trade policy data.

I use the publicly available version of MECS. In measuring energy consumption as fuel in trillion BTU, I assume that suppressed values less than 0.5 (denoted with an asterisk) equal zero. For withheld cells (denoted by Q or W), I impute the value as manufacturing's overall share of BTU from a fuel, multiplied by the industry's total BTUs.

The paper's main approach to measuring total emissions involves inverting an input-output table. The diagonal of an input-output table, which generally has the largest values in an input-output table, describes outputs from an industry that are used to produce output in the same industry. This implies that fossil fuels which are used to produce fossil fuels (e.g., oil used to power a drill that is used to extract oil) are captured in this approach since they appear on the diagonal of the input-output table.

Appendix Figure 1, Panel C, plots the density of these total CO_2 emission rates, separately for all global trade and for all U.S. imports. For U.S. and global trade, the median CO_2 emission rate is 0.5 to 1.0 tons CO_2 per thousand dollars of output. Emissions rates for the U.S. have a longer right tail since the U.S. data have more industry detail.

B Implicit Carbon Tariffs: Sensitivity Analyses

Appendix Table 1 reports numerous other estimates of the implicit CO_2 subsidies. Row 1 repeats the main estimates from Tables 2 and 3. Row 2 reports marginal effects from a tobit,

[6] Data from https://www.epa.gov/sites/production/files/2018-03/documents/emission-factors_mar_2018_0.pdf, visited 11/19/2019.

since some industries have zero tariffs or NTBs. Row 3 reports an instrumental variables tobit where direct CO_2 intensity is the instrument for total CO_2 intensity. Row 4 clusters standard errors by the importing country.

Rows 5-7 report estimates that allow for nonlinear effects of CO_2. Row 5 estimates the dependent and independent variable in logs, and so estimates an elasticity. This specification excludes observations with zero tariff or NTB. Row 6 specifies the CO_2 rate as a quadratic polynomial, and reports estimates of the slope $\partial t/\partial E$ at the 10th, 50th, and 90th percentile of the distribution of CO_2 values. Row 7 estimates a nonparametric regression (a third-order B-spline) and reports the average marginal effect.

Rows 8-15 report other ways of cleaning and aggregating data. Row 8 replaces the bottom and top percent of the dependent and independent variables as equal to the 1st and 99th percentile values. Row 9 includes non-manufactured goods (agriculture and mining), alongside the manufactured goods analyzed in most of the paper. Row 10 uses a dataset defined at the level of a bilateral trading pair and industry (i×j×s rather than j×s). Row 11 uses the same approach but adds exporter fixed effects.[7] Row 12 aggregates to one industry per observation. Row 13 includes intra-national trade ($i = j$) in the measurement of emissions rates, with an intra-national tariff and NTB rate of zero.

Rows 14-16 use other measures of emissions. Row 14 considers only direct emissions, measured from the input-output table. Row 15 includes both the direct and total emissions, both measured from the input-output table. Row 16 uses data on all greenhouse gases and sources in Exiobase, including nitrous oxide (N_2O), methane (CH_4), and emissions of each greenhouse gas from non-combustion processes.

Rows 17-19 consider other ways of measuring the emissions rate of energy-consuming durable goods. The baseline regressions ignore emissions from goods that are complements or substitutes with the focal good. For example, changing tariffs on cereal might change consumption of milk, but the energy intensity of cereal in this analysis does not account for the energy intensity of milk. While estimating a flexible demand system of many cross-elasticities across goods in the global economy is beyond the scope of this paper, measuring emissions from consumption is potentially most important for durable goods that require energy to operate, including transportation goods like cars and appliances like air conditioners.[8] For these goods especially, abstracting from the energy that is complementary to consuming these goods provides an incomplete picture of the emissions due to trading these goods. This is relevant because energy-consuming durables are relatively downstream and are relatively clean according to the approach of this paper.

Rows 17-19 take two approaches for energy-consuming durables. Row 17 excludes energy-consuming durable household goods from the analysis, including machinery and equipment

[7] One alternative candidate explanation for tariff escalation is that countries offer preferential market access to developing countries, which specialize in upstream goods. Under this explanation, controlling for exporter fixed effects would attenuate both tariff escalation and implicit tariffs. The estimates of row 11, which include these fixed effects, are actually larger in absolute value than the estimates of row 10, which do not use these fixed effects, which could suggest that this candidate explanation is not the predominant driver of tariff escalation or of the environmental bias of trade policy.

[8] The question of how to account for emissions from consumption versus production of international services trade, such as international airplane flights, is also important. Because tariffs do not apply to trade in services, and because the Kee et al. (2009) data I use on NTBs cover goods and not services, I leave the analysis of NTBs involving services and the environment to future research.

not elsewhere classified (a category including appliances), motor vehicles, trailers, semi-trailers, and other transport equipment. Row 18 assumes that the emissions rate for these durable goods is an unweighted average of the emission rate for these durable goods and the emission rate for energy in the importing country. Row 19 assumes that the emission rates for these goods is a weighted average of the emission rate for these goods and for energy in the importing country, with weights of 5 percent and 95 percent, respectively. The emission rate for energy averages over petroleum refining, natural gas extraction, and all forms of electricity production, where weights equal the gross output of each industry in the importing country. These different weighting schemes reflect evidence on the importance of emissions from manufacturing versus operation for these goods (Union of Concerned Scientists 2013; Nahlik et al. 2015; Amienyo et al. 2016).

Rows 20 through 25 show other sensitivity analyses. Row 20 shows the reverse regression of emissions rates E on trade policy t. Row 21 replaces the usual tariff measure on goods, dt, with a life cycle measure $(I-A)^{-1}dt$. This accounts for tariffs on inputs, and inputs to inputs, etc. Row 22 estimates the regression without importer fixed effects. Row 23 uses data from the World Input Output Dataset (WIOD). Row 24 adds industry fixed effects. Row 25 excludes manufactured agricultural goods and manufactured food products.

Most results in Appendix Table 1 are similar to the main estimates, though some vary in their magnitudes. I highlight some of the more important differences here. Tobit estimates obtain larger estimates of implicit subsidies for NTBs but not tariffs, since more observations have zero NTBs. The estimates that allow for nonlinearity in CO_2 rates generally find negative slope, though the magnitude differs across the support of CO_2 rates—the quadratic estimates in row 6, for example, imply a wide range of estimated global subsidies, while nonparametric estimates in row 7 imply a global subsidy of about \$100/ton. Incorporating intra-national trade (row 13) modestly increases the weighted but decreases the unweighted estimates in absolute value. Direct emissions have a similar association with trade policy as total emissions do; when a regression includes both, the coefficient on total emissions accounts for more of the total subsidy, though neither estimate is precise, perhaps in part due to multicollinearity. Excluding energy-consuming durable goods from the analysis or adjusting emission rates of these goods to account for energy used in their consumption does not substantially change the estimated subsidy in absolute value. The reverse regression has smaller coefficients since it reverses the dependent and independent variables. The WIOD data still imply subsidies but are imprecise, partly because they only have 15 tradable manufacturing industries. Adding industry fixed effects nearly eliminates the implicit subsidy. This is perhaps unsurprising since industry-level estimates in row 12 are similar to baseline estimates in row 1, though this does suggest that whatever economic forces create these subsidies operate at the industry level and are similar within an industry and across countries. Excluding agricultural and food manufactured products produces smaller estimates of the implicit subsidies.

Appendix Table 1, rows 26-27, focus on the recent trade war by analyzing U.S. import tariffs at the end of 2018. Row 26 estimates the implicit subsidy for U.S. import tariffs using tariff data from 2017, as in Figure 2. Row 27 augments these data with the sum of five rounds of tariffs imposed in 2018, which targeted washers, solar panels, aluminum, and Chinese imports. I measure these tariffs using data from Fajgelbaum et al. (2020). Unweighted estimates show a modest decrease in trade policy's environmental bias, of nearly a dollar a ton, while weighted estimates show a smaller increase. These estimates are mixed because while much attention focused on dirty goods like aluminum or steel, the most CO_2-intensive goods like refined petroleum and cement did not experience tariff changes in this time period. Some goods with larger increases in tariffs in this period, like semiconductor manufacturing or laundry equipment manufacturing, are not especially CO_2-intensive.

C Informal Discussion of Trade Policy Theories

This Appendix informally discusses how theories of trade policy might rationalize the paper's findings. It is useful to distinguish two reasons why countries choose trade policy. One is to exploit market power and terms-of-trade externalities. Another is to satisfy domestic industries which lobby for high tariffs on their output.

Some trade policy instruments, like NTBs and non-cooperative tariffs, are chosen independently by countries and are typically not negotiated with other countries. In theories of explaining such non-cooperative trade policy (Grossman and Helpman 1994; Goldberg and Maggi 1999), both the terms-of-trade externality and political economy forces determine tariffs. In these frameworks, governments value the welfare of their citizens, which decreases overall with protection, but governments also value campaign contributions and other support from industry, which increases with the protection industries receive. These frameworks can accommodate industries' lobbying for low tariffs on industries they use as intermediate inputs (Gawande et al. 2012). The finding of implicit carbon subsidies in non-cooperative policy instruments, and the empirical relevance of upstreamness, are consistent with these theories.

Other trade policy instruments, like most tariffs, are cooperatively chosen by countries through negotiation. Research has provided two broad explanations for why countries cooperate on trade policy (Grossman and Helpman 1994; Maggi and Rodríguez-Clare 1998, 2007). One is that cooperation helps decrease terms of trade externalities, though not necessarily the political economy components of trade policy. A second explanation for cooperation is that governments understand the political pressure of trade lobbies and the welfare costs of protection. In this explanation, governments commit to free trade agreements in order to tie their hands and obtain a more efficient domestic allocation of resources across industries, while limiting the resulting political cost.

In all these cooperative theories, political economy motives like lobbying for low upstream tariffs potentially remain an important determinant of non-cooperative and cooperative trade policy. In Grossman and Helpman (1995), cooperation does not change political economy motives for trade policy. In the commitment theory, negotiation may attenuate but not eliminate political economy's effects on trade policy. These interpretations suggest that lobbying competition between upstream and downstream industries may occur in both cooperative and non-cooperative policies, and extends beyond any single model.

Another general interpretation of this is as follows. A goal of cooperative trade policy negotiation (e.g., through the World Trade Organization) is to eliminate one externality – the terms-of-trade motive for trade policy – which leaves political economy motives remaining. This paper highlights that those negotiations, however, leave a second externality untouched—an environmental externality which arises from political economy forces behind trade policy.

To be concrete about why counter-lobbying might create tariff escalation, consider the example of a fairly upstream industry like steel and a fairly downstream good like cigarette manufacturing. Many industries use steel as an input, either directly (they purchase steel) or indirectly through global value chains (they purchase goods which use steel as an input, or goods which use inputs which use steel as an input, etc.). Hence, many industries will lobby for low tariffs and low NTBs on steel. By contrast, few industries use cigarettes as an input, and hence few industries will lobby for low tariffs or low NTBs on cigarettes. Final consumers might prefer low tariffs and low NTBs on both steel and cigarettes, but final consumers are less well organized than industries, and hence have less lobbying influence. Thus, countries end up with lower tariffs or NTBs on steel, and higher tariffs or NTBs on tobacco products.[9]

Finally, it is worth discussing one potential explanation from public finance. Diamond and Mirrlees (1971) consider commodity taxation in a general setting. Even in a second-best world where the government uses (distortionary) linear commodity taxes, which imply that the first-best Pareto optimal outcome is infeasible, they show that the optimal tax system maintains the economy at the production possibilities frontier. A corollary is that optimal commodity taxes apply only to final and not intermediate goods.[10]

Based on this theorem, one might conjecture that tariff escalation has an efficiency rationale. This interpretation might claim that downstream goods are final goods, and that tariff escalation seeks to maintain production efficiency by putting tariffs on final rather than intermediate goods. In this interpretation, while upstreamness accounts for trade policy's environmental bias, the link between upstreamness and trade policy could be caused by government's desire for an efficient tax system rather than by lobbying. Additionally, if tariff escalation reflected efficiency rather than political economy forces, then harmonizing tariffs between upstream and downstream goods could decrease production efficiency even if it benefited the environment.

Two reasons suggest that production efficiency does not explain the prevalence of tariff escalation. First, I find similar escalation in NTBs as in tariffs. NTBs do not raise revenue, so optimal taxes would not include NTBs, except to the extent that they address market failures. Hence, production efficiency does not explain why NTBs exist or have escalation. Second, the production efficiency theorem does not rank the efficiency of different second-best tax systems by the degree to which they tax intermediate goods. This theory does not permit stating that a tax or tariff structure which has more escalation is more efficient; it merely states that the optimal tax system has no taxes on intermediate goods.[11]

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[9] In the global data, weighted across countries by the value of imports, steel has a mean upstreamness value of 3.5, tariff of 1.3 percent, and NTB ad valorem equivalent of 1.5 percent. Tobacco products has upstreamness of 1.2, tariff of 9.8 percent and NTB ad valorem equivalent of 43 percent. These are among the most and least upstream industries in Exiobase.

[10] One intuitive explanation is that under constant returns to scale, any tax on intermediate goods would appear through changes in final goods prices. Then the government could collect the revenue through this tax on final goods. But because taxing intermediate goods prices distorts firms' input choices, it moves the economy away from production efficiency (Diamond and Mirrlees 1971, p. 24).

[11] A related potential explanation is that distortions in the economy aggregate through upstream input purchases, so an efficient industrial policy would subsidize upstream sectors (Liu 2018). This interpretation would argue for direct production subsidies rather than trade policies, and it also would not apply to an

D General Analytical Model

To study the effects of trade policy's environmental bias, I use a simple two-country, two-good model that incorporates existing ideas (Markusen 1975; Copeland 1994; Kortum and Weisbach 2019). This model encompasses several potentially important features: pollution can directly affect utility; pollution has transboundary damages; consumers may have non-homothetic preferences; policy reforms may occur from a sub-optimal baseline; and large countries may affect world prices.

I consider two countries: A (Home) and B (Foreign), indexed by i. They may trade two goods: 0 (clean) and 1 (dirty), indexed by s.

Preferences. Let C_s^i denote the consumption of good s in country i. Let Z denote global CO_2 emissions. The utility of the representative agent in country i is $W^i = W^i(C_0^i, C_1^i, Z),\ \ i \in (A, B)$.

Technology. Let X_s^i denote the quantity of good i produced in country i. Let $F^i(\cdot)$ denote the production possibilities frontier: $F^i(X_0^i, X_1^i) = 0,\ \ i \in (A, B)$. We can also write the frontier as $X_0^i = T^i(X_1^i)$.

Pollution. Global pollution emissions increase with output of the dirty good in each country: $Z = Z(X_1^A, X_1^B)$.

Equilibrium. Let good 0 be the numeraire, let p denote the price ratio of good 1 to good 0 in country A, and let p^* denote this price ratio in country B. Country A may impose a trade tax rate of t on good 1, implying

$$p^*(1+t) = p \tag{2}$$

If country A imports good 1 and $t > 0$, then this tax rate t is an ad valorem import tariff. If country A exports good 1 and $t > 0$, then this tax rate t is an export subsidy. In both cases, the taxes raises the domestic price p relative to the foreign price p^*.

The first order conditions are useful for deriving comparative statics. Production efficiency implies that producers equate the ratio of their marginal products to the price ratio:

$$p = \frac{\partial F^A/\partial X_1^A}{\partial F^A/\partial X_0^A} = -\frac{\partial T(X_1^A)}{\partial X_1^A}, \qquad p^* = \frac{\partial F^B/\partial X_1^B}{\partial F^B/\partial X_0^B} = -\frac{\partial T(X_1^B)}{\partial X_1^B} \tag{3}$$

I assume $T(\cdot)$ is strictly concave. Consumption efficiency implies that consumers equate the marginal ratio of substitution to the price ratio:

$$p = \frac{\partial W^A/\partial C_1^A}{\partial W^A/\partial C_0^A}, \qquad p^* = \frac{\partial W^B/\partial C_1^B}{\partial W^B/\partial C_0^B}$$

Define country A's net exports of good s as $e_s \equiv X_s^A - C_s^A$. Trade balance implies $e_0 + p^* e_1 = 0$.

Comparative Statics: **Pollution**. To study how policy affects pollution, totally differentiate the pollution equation $Z = Z(X_1^A, X_1^B)$:

$$dZ = \frac{\partial Z}{\partial X_1^A} dX_1^A + \frac{\partial Z}{\partial X_1^B} dX_1^B \tag{4}$$

undistorted economy already at the first-best.

I relate this to policy changes through a few steps. First, differentiate the production efficiency condition (3), define $R^n \equiv -[\partial^2 T(X_1^i)/\partial X_1^i]^{-1}$, and substitute into the pollution derivative (4). Combining this with the total derivative of the price equation (2) gives

$$dZ = d(1+t)\left[\frac{\partial Z}{\partial X_1^A} R^A p^*\right] + dp^*\left[\frac{\partial Z}{\partial X_1^B} R^B + \frac{\partial Z}{\partial X_1^A} R^A (1+t)\right] \tag{5}$$

The terms in equation (5) that include $\partial Z/\partial X_1^A$ represent the change in home country pollution emissions due to changes in the home country's trade policy. The term including $\partial Z/\partial X_1^B$ represents a change in foreign pollution emissions due to changes in the home country's trade policy.

To interpret equation (5), consider first a small open economy, for which policy cannot change world prices (so $dp^* = 0$). Here, increasing the trade tax on dirty goods ($d(1+t) > 0$) unambiguously increases global emissions. We can sign the result since prices are positive ($p^* > 0$), pollution increases in both its arguments ($\partial Z/\partial X_1^A > 0$), and $R^A>0$ due to the strict concavity of $T(\cdot)$. This result has an intuitive explanation. If a small open economy raises tariffs on dirty goods, it increases these goods' domestic price without changing their world price. Domestic production shifts towards the dirty industry in response to the price change, but foreign production does not (since world prices are fixed here by assumption). Of course, a marginal policy change in a small open economy will have small effects on global emissions.

Results are more ambiguous for a large economy. The first bracketed term in equation (5) again represents the effect for a small open economy and is positive. The second term is negative, because tariffs t are nonnegative, emissions increase in both their arguments ($\partial Z/\partial X_1^i > 0$), and the technology terms are positive ($R^i > 0$). The key difference in the second term is that a large economy's import tariff decreases world prices, so $dp^* < 0$. Intuitively, this policy reform decreases foreign emissions since it decreases foreign prices of dirty goods. This can also be seen from a simpler version which assumes both countries have the same emissions and production technology; for this simpler case we get $dZ = (\partial Z/\partial X_1)R(dp + dp^*)$; here every term is positive except dp^*.

Differentiating equation (5) with respect to each argument shows that the following forces each make a large country's tariffs on dirty goods decrease global emissions more (or increase them less). First, this occurs when a country has market power and increasing tariffs on imports of dirty goods causes a relatively large decrease in world prices (dp^* is large). Second, this occurs when foreign production is especially dirty ($\partial Z/\partial X_1^B$ is large). This is relevant since many countries outsource production of dirty goods to countries that are coal-intensive in production, such as China, and since international trade requires emissions for international transportation, which is pollution-intensive. Third, this occurs in settings with higher baseline tariffs on dirty goods ($1 + t$ is large). Finally, this occurs in settings where foreign production technology is especially concave (R^A is large). This concavity captures the extent to which decreasing the relative price of dirty goods makes the economy substitute from dirty to clean production.

Comparative Statics: Welfare. To study how policy affects welfare, totally differentiate utility:

$$\frac{dW^i}{\partial W^i/\partial C_0^i} = dC_0^i + \frac{\partial W^i/\partial C_1^i}{\partial W^i/\partial C_0^i} dC_1^i + \frac{\partial W^i/\partial Z}{\partial W^i/\partial C_0^i} dZ$$

To write in terms of policy changes, define the social cost of pollution as $\delta^i \equiv (\partial W^i/\partial Z)/(\partial W^i/\partial C_0^i)$ and write the foreign price as a function of Home's net exports $p^* = E(e_1)$. Then calculate total derivatives of the definition of net exports, the trade balance condition, the transformation function, and the definition of foreign price as a function of Home's net exports. Combining these results with production efficiency gives the main result that can be used to study welfare:

$$\frac{dW^i}{\partial W^i/\partial C_0^A} = \left[\frac{\partial p^*}{\partial e_1} e_1 - p^* t\right] de_1 + \delta^i dZ \tag{6}$$

This is essentially the expression used to derive the optimal tariff in Markusen (1975), although the setting is slightly different. Ignoring pollution by setting $\delta^i = 0$, this would imply the standard result that the (privately) optimal tariff equals the inverse export supply elasticity, which can be found by setting $Z = de_1 = 0$: $t^{optimal} = (\partial p^*/\partial e_1)(e_1/p^*)$. If the dirty good is imported, increasing import tariffs increases national welfare when baseline tariffs are below the optimum, and decreases it when baseline tariffs are below the optimum.

Because pollution creates global damages, accounting for pollution creates the same patterns of effects as in equation (5)—changing policy affects both domestic emissions (the last term in equation (6)) and foreign emissions (the second term in this equation). The effect of trade policy on welfare here is separable into a traditional term capturing the gains from trade, and a separate term reflecting pollution damages.

This simple model captures two important ideas about how increasing protection can affect global emissions, though misses others. Any one country's protection can increase domestic emissions. Since this model has only two goods, it does not accommodate intra-industry trade, and two countries cannot simultaneously impose import tariffs on dirty goods. In reality, if all countries increase tariffs on dirty goods, production of dirty goods could fall in all countries, which does not occur from trade policy in a two-good model. Additionally, because it analyzes small perturbations of existing policy, this abstracts from changes in the scale of global output. For these and other reasons, the main text discusses analytical results from a model where goods differ by country of origin.

E Quantitative General Equilibrium Model

I show an Armington model for simplicity and comparability with the 2×2 model in the main text. A richer Ricardian model (e.g., Eaton and Kortum 2002) would lead to the same equilibrium equations and hence the same counterfactual results.

Assumption 1 (Preferences): Each country produces one variety per sector. The representative agent in each destination country j has constant elasticity of substitution preferences across the varieties and Cobb-Douglas preferences across sectors s:

$$U_j = \prod_s \left(\sum_i q_{ijs}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}\beta_{js}} [1 + \delta(Z - Z_0)]^{-1} \tag{7}$$

Here q_{ijs} is the quantity of the variety from country i and sector s consumed in country j, $\sigma_s > 1$ is the elasticity of substitution, and β_{js} is the Cobb-Douglas expenditure share. The bracketed term on the right captures the disutility from climate change; δ represents a damage parameter, Z_0 represents a reference or baseline level of global CO_2 emissions used to calibrate the damage parameter, and Z represents the global emissions in a particular model scenario.

Several reasons support using this functional form for climate damages. It makes damages multiplicative, which facilitates the analysis of counterfactuals using ratios. It also makes damages proportional to real income. It permits calibration of the climate damage parameter δ so that a one-ton increase in CO_2 emissions decreases global welfare by \$40, which corresponds with prevailing estimates from the climate change literature (IWG 2016). Additionally, it provides a simple functional form to accomplish these objectives. This specification is designed to measure damages from changes in emissions only, since in baseline data, $Z = Z_0$, so the model abstracts from baseline climate damages.

Assumption 2 (Firms and Production Technology): Goods are produced with a Cobb-Douglas combination of the factor L and an aggregate intermediate good, which is a constant elasticity of substitution combination of varieties of intermediate goods:

$$a_{jt} = (L_{jt})^{1-\eta_{is}} \prod_s \left(\sum_o {q^I_{ojst}}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}\eta_{jst}} \tag{8}$$

The aggregate intermediate good is CES in varieties q^I_{ijst} shipped from origin country i and origin industry s to destination country j and destination industry t, and is Cobb-Douglas across industries. Here η_{jst} is the intermediate goods share of industry s for production of industry t in country j.

Buyers pay variable trade costs $\phi_{ijt} \equiv \tau_{ijt}(1+t_{ijt})(1+n_{ijt})$. Here $\tau_{ijt} \geq 1$ are iceberg trade costs, so τ goods must be shipped for one to arrive; I normalize $\tau_{jjt} = 1$. Additionally, buyers pay bilateral import tariffs t_{ijs}; tariff revenues are lump-sum rebated to domestic consumers. I treat NTBs n_{ijs} as a multiplicative tariff with revenue that is lost (or, equivalently, as a form of iceberg trade cost). The quantitative application of this model includes a non-traded sector; one could interpret this as a sector within infinite trade costs.

Assumption 3 (Pollution): CO_2 emissions equal $Z_{is} = \gamma_{is} R_{is}/P_{is}$. Here Z_{is} are the tons of CO_2 emitted due to producing goods from industry s in country i, R_{is} is country×sector revenue, and P_{is} is the country×sector price index. The coefficient γ equals the tons of CO_2 per real unit of output in country i and sector s. This variable γ equals zero for all industries besides coal extraction, oil extraction, and natural gas extraction. For these three fossil fuel extraction industries, γ equals the metric tons of CO_2 per real dollar of output of a given fossil fuel in a given country.

Assumption 4 (Market Clearing): Market clearing for labor and trade balance are $L_i = \sum_s L_{is}$ and $\sum_{j,s} X_{ijs} = \sum_{j,s} X_{jis} - D_i$. Here L_{is} is factor supply, D_i are trade deficits, and X_{ijs} is expenditure flows. I assume that in baseline data and in any counterfactual, consumers maximize utility, firms maximize profits, and markets clear, so the data describe a competitive equilibrium.

These equations complete the model, and imply several results useful for quantification. The cost to produce one unit of output is

$$c_{is} = w_i^{1-\eta_{is}} \prod_k P_{ik}^{\eta_{iks}}$$

This unit cost is Cobb-Douglas in the price of factors w_i and intermediates, and also Cobb-Douglas across the price index of intermediates P_{ik}. Sector s in country j has the following price index:

$$P_{js} = \left(\sum_i (\phi_{ijs} c_{is})^{\epsilon_s} \right)^{\frac{1}{\epsilon_s}}$$

Here the price index depends on trade barriers ϕ_{ijs}, unit costs c_{is}, and I write equilibrium equations in terms of the trade elasticity $\epsilon_s < 0$, which is related to the elasticity of substitution by $\epsilon_s \equiv \sigma_s - 1$.

The share of a country's expenditure in a given sector which is allocated to a specific exporter is $\lambda_{ijs} \equiv X_{ijs}/X_{js}$, where X_{ijs} is the value of bilateral trade. Consumer utility maximization implies that this can be written as follows:

$$\lambda_{ijs} = \frac{(\phi_{ijs} c_{is})^{\epsilon_s}}{\sum_o (\phi_{ojs} c_{os})^{\epsilon_s}}$$

This is a standard "gravity" equation.

Total expenditure on varieties from sector s in country j equals the Cobb-Douglas expenditure share β_{js} times total income from factors, trade deficits, and tariffs, plus income from selling intermediate goods:

$$X_{js} = \frac{\beta_{js} \left(Y_j + D_j + \sum_{i,l} \frac{t_{ijl}}{1+t_{ijl}} \lambda_{ijl} \sum_k \alpha_{jlk} R_{jk} \right)}{1 - \sum_{i,l} \frac{t_{ijl}}{1+t_{ijl}} \lambda_{ijl} \beta_{jl}} + \sum_k \alpha_{jlk} R_{jk}$$

Revenues for a given country and sector equal pre-tariff bilateral trade, summed over destinations:

$$R_{is} = \sum_j \frac{\lambda_{ijs}}{1+t_{ijs}} X_{js}$$

By the Cobb-Douglas assumption of the production technology, labor income is a constant share of total revenues:

$$Y_i = \sum_s (1-\alpha_{is}) R_{is}$$

I rewrite these equations in changes, which produces a system of nonlinear equations. These equations describe a competitive equilibrium. I now consider how a counterfactual policy would affect this equilibrium. This counterfactual analysis uses the "exact hat algebra" of Dekle et al. (2008). The cost function is the proportional change in wages and intermediate goods prices, scaled by their Cobb-Douglas expenditure shares:

$$\hat{c}_{is} = \hat{w}_i^{1-\eta_{is}} \prod_k \hat{P}_{ik}^{\eta_{iks}}$$

The change in the price index is the weighted sum of bilateral prices from each possible exporter, where weights equal the baseline expenditure shares λ_{ijs}:

$$\hat{\lambda}_{ijs} = \frac{(\hat{\phi}_{ijs}\hat{c}_{is})^{\epsilon_s}}{\sum_o \lambda_{ojs}(\hat{\phi}_{ojs}\hat{c}_{os})^{\epsilon_s}}$$

The change in a country's expenditure on a given sector can be written as

$$\hat{X}_{js}X_{js} = \frac{\beta_{js}\left(\hat{w}_j Y_j + D_j + \sum_{i,l}\frac{t'_{ijl}}{1+t'_{ijl}}\hat{\lambda}_{ijl}\lambda_{ijl}\sum_k \alpha_{jlk}\hat{R}_{jk}R_{jk}\right)}{1-\sum_{i,s}\frac{t'_{ijs}}{1+t'_{ijs}}\hat{\lambda}_{ijs}\lambda_{ijs}\beta_{js}} + \sum_k \alpha_{jsk}\hat{R}_{jk}R_{jk}$$

The change in a country's revenue from a given sector can be written as

$$\hat{R}_{is}R_{is} = \sum_j \frac{\hat{\lambda}_{ijs}\lambda_{ijs}}{1+t'_{ijs}}\hat{X}_{js}X_{js}$$

Finally, the change in national income is

$$\hat{Y}_i Y_i = \sum_s (1-\eta_{is})\hat{R}_{is}R_{is}$$

For baseline data, these equations hold exactly. Under counterfactual tariffs or NTBs, I solve this system to find the changes in prices and firm entry that make it hold with equality. Finally, I use these to find the resulting change in real income, pollution, and social welfare:

$$\begin{aligned}
\hat{V}_j &= \frac{Y_j \widehat{+ D_j} + T_j}{\hat{P}_j} \\
\hat{Z}_i &= \frac{\sum_s \gamma_{is}\hat{R}_{is}R_{is}/\hat{P}_{is}P_{is}}{\sum_s \gamma_{is}R_{is}/P_{is}} \\
\hat{W}_j &= \frac{\hat{V}_j}{[1+\delta(Z'-Z_0)]}
\end{aligned}$$

This uses the notation $\hat{x} = x'/x$, where x is some variable in the baseline data, x' is its value in a counterfactual, and $\hat{x}$ is the proportional ratio between the two. Here T_j is total tariff revenue.

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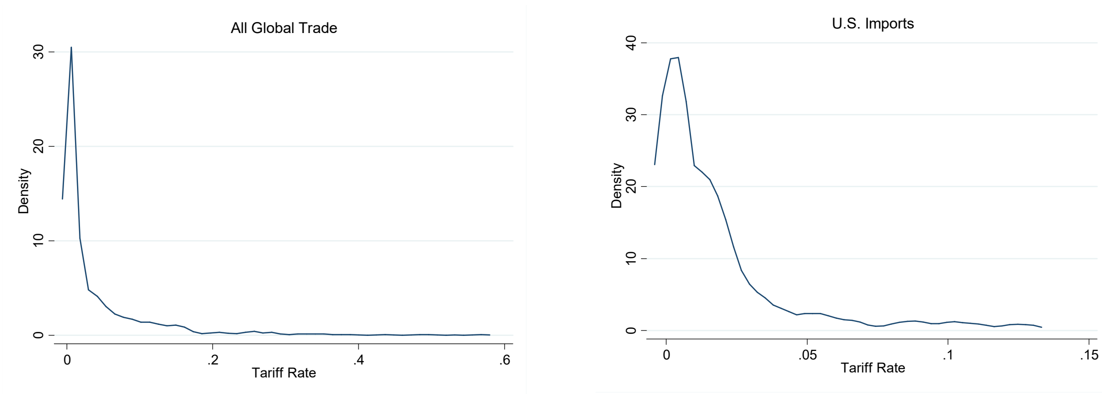
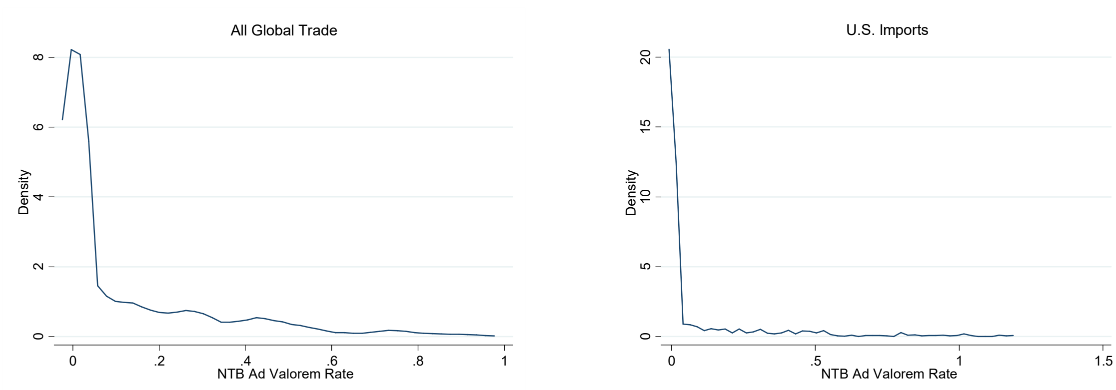
Appendix Figure 1—Densities of Trade Policy, Carbon Intensity, and Upstreamness

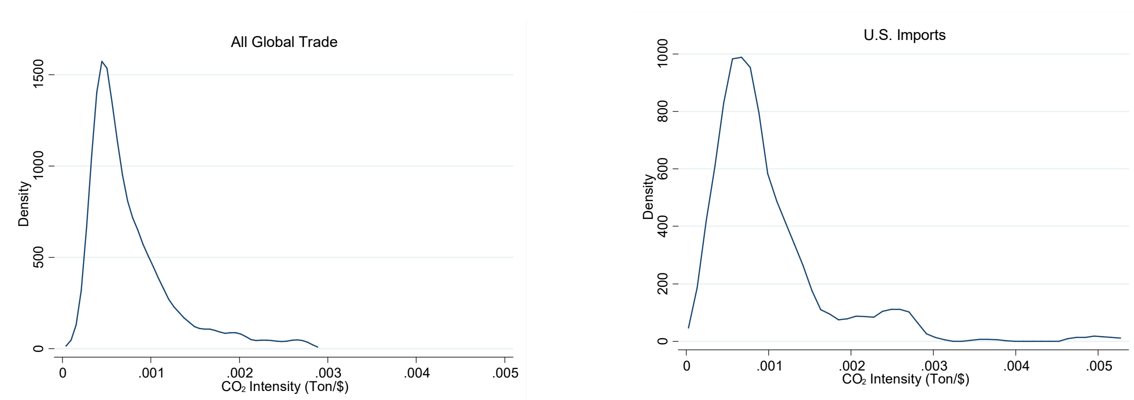
Panel A. Density of tariffs



Panel B. Density of non-tariff barriers



Panel C. Density of Total CO_2 intensity



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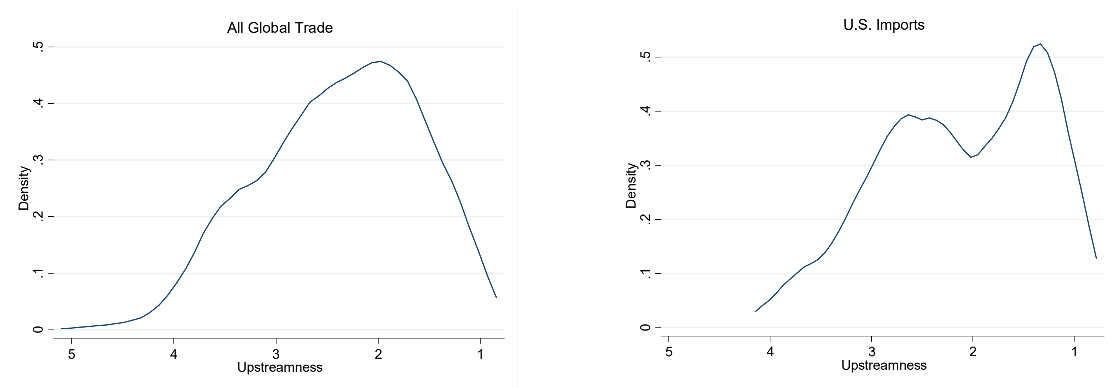
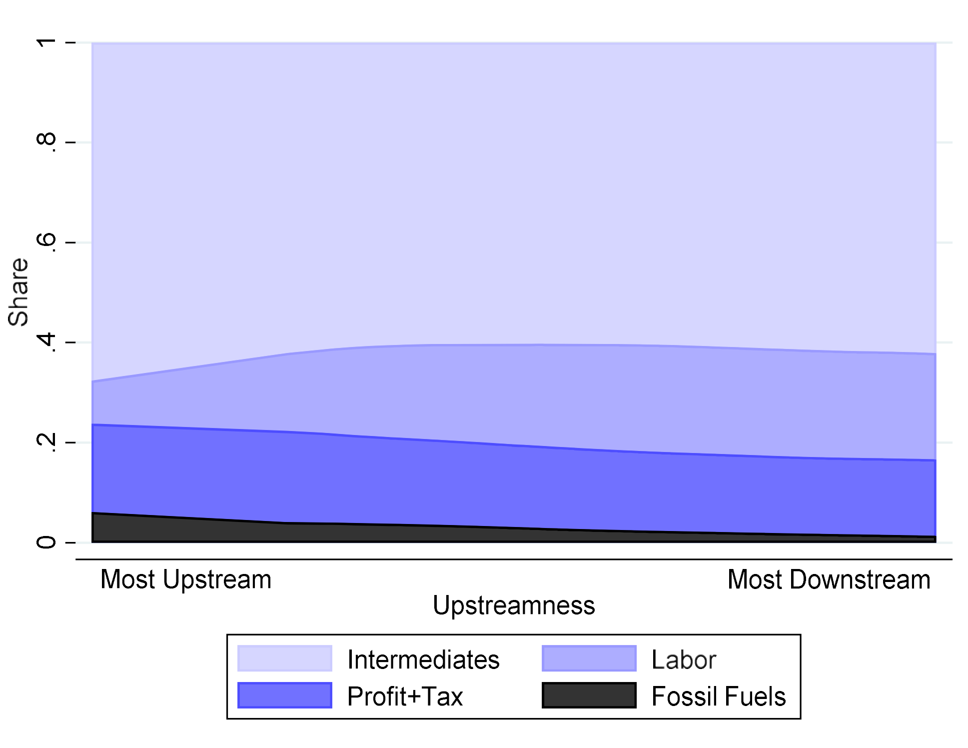
Appendix Figure 1—Densities of Trade Policy, Carbon Intensity, and Upstreamness (Continued)

Panel D. Density of upstreamness



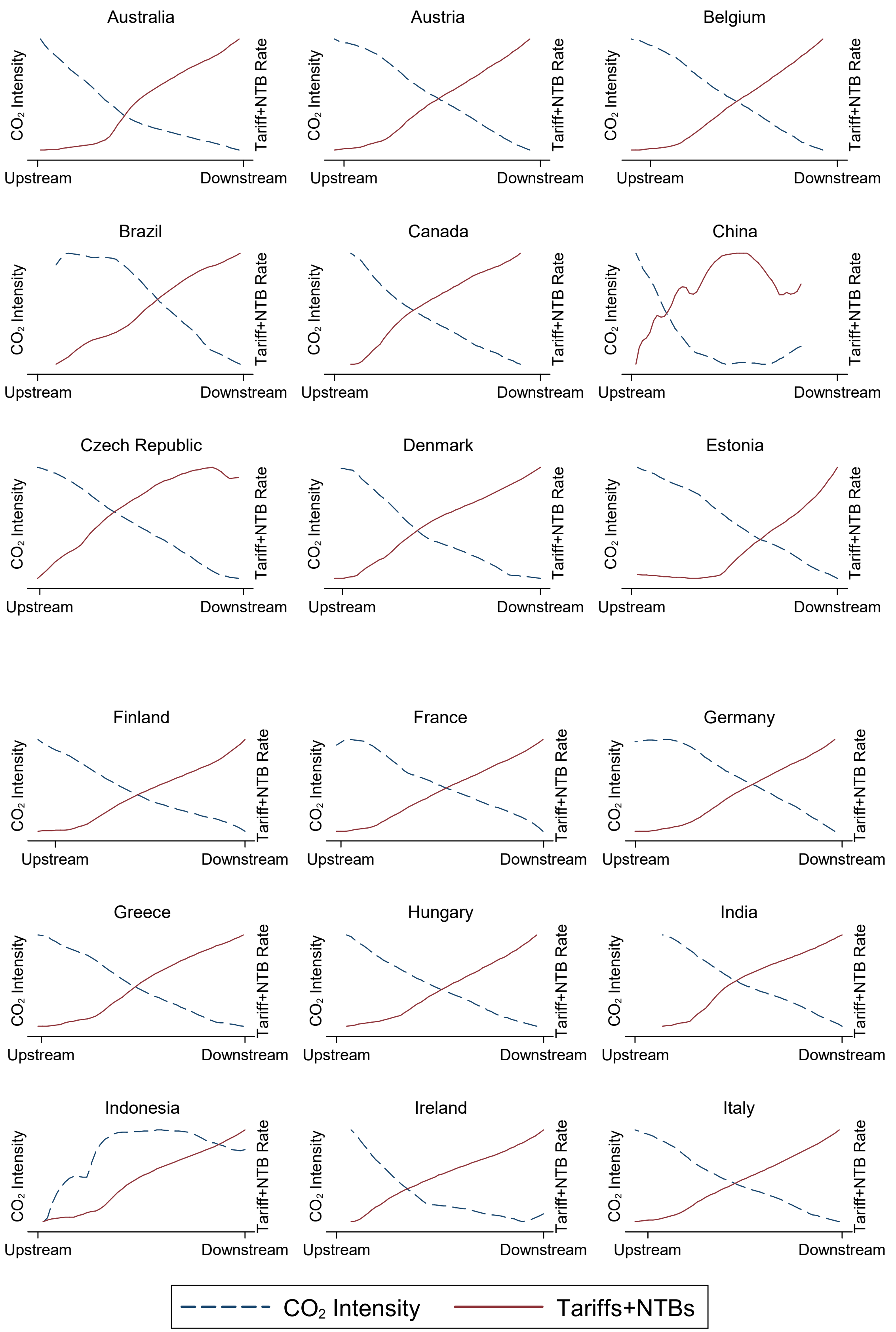
Notes: Graphs exclude top 1% of each variable. The value 5 represents the most upstream, while 1 is the least upstream. Upstreamness measured as in Antràs et al. (2012).

Appendix Figure 2—U.S. Upstreamness and Components of Revenues

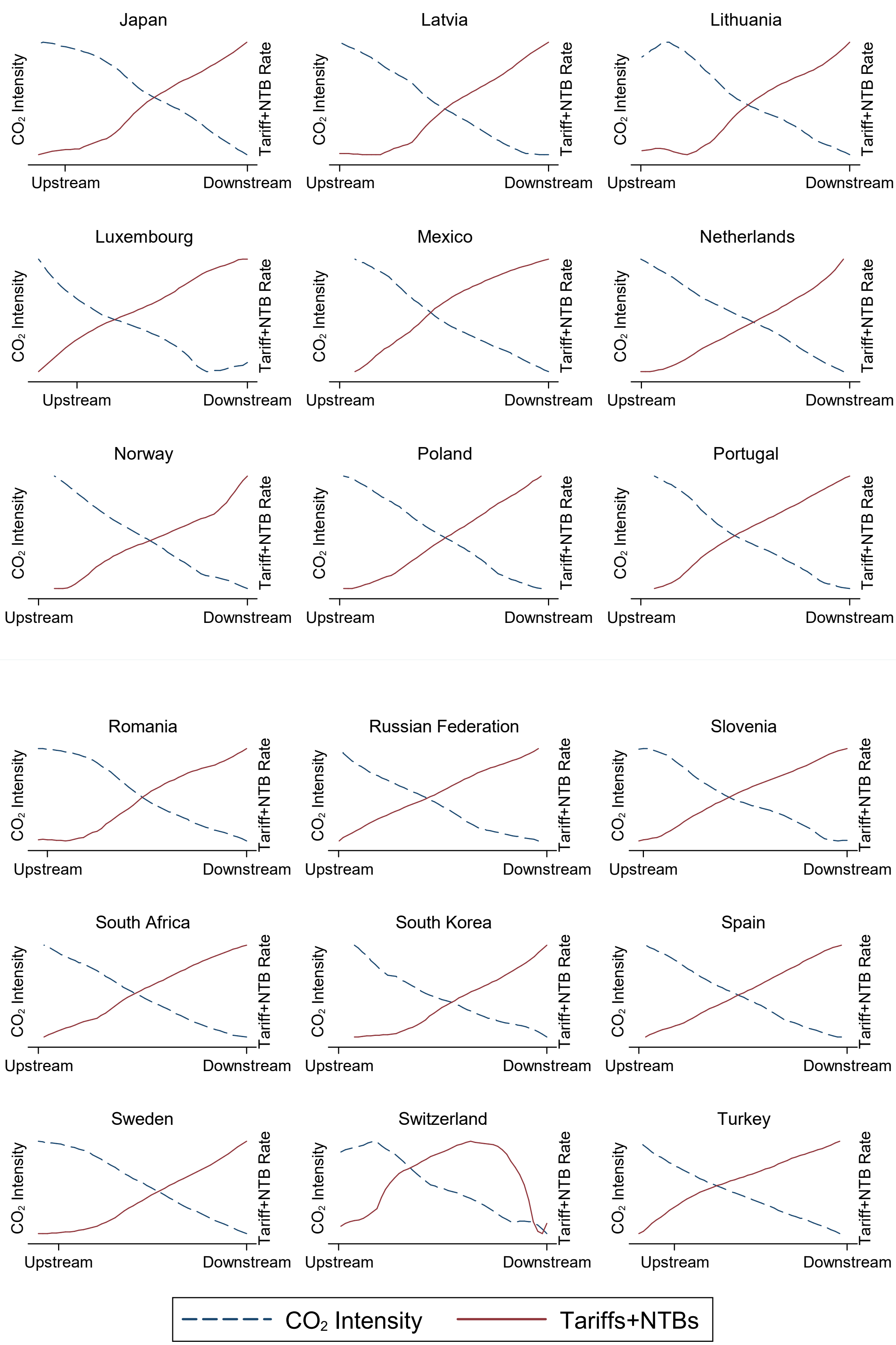


Notes: Data from the U.S. BEA use table for year 2007. Fossil fuel industries include natural gas distribution, oil and gas extraction, electricity generation, petroleum refineries, and coal mining. For smoothness, for each component of output separately, this analysis estimates a local linear regression of the relevant component on upstreamness. The graph shows the fitted values from these regressions. The y-axis is the share of an industry's total value of shipments which is accounted for by each of the four listed components. The graph describes only manufacturing outputs (though counts intermediate inputs from all industries).

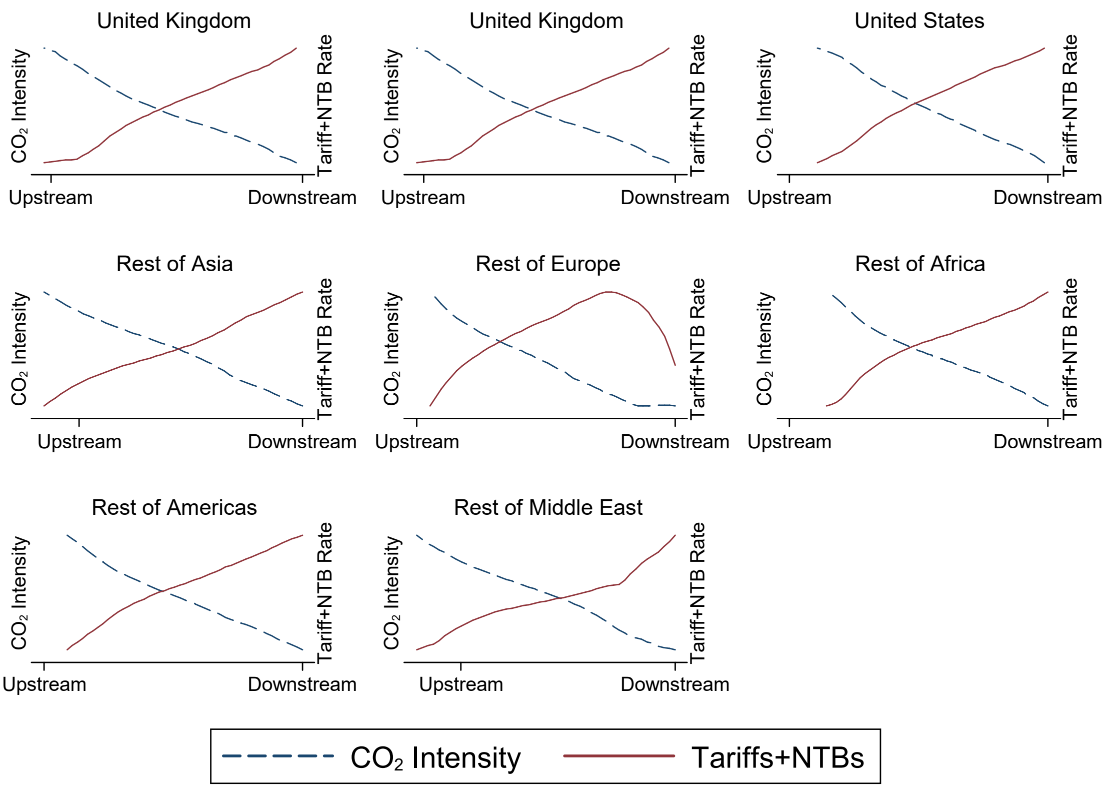
Appendix Figure 3—Upstream Location, CO_2 Intensity, and Trade Policy, by Country



Appendix Figure 3—Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)



Appendix Figure 3—Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)



Notes: in each graph, the solid red line is from a local linear regression of import tariffs on the industry's upstreamness. The dashed blue line is from a local linear regression of CO_2 intensity on the industry's upstreamness. Upstreamness is the simple measure of the share of an industry's output sold to other industries as intermediate goods (rather than as final demand). All data from Exiobase. All regressions use an Epanechnikov kernel with bandwidth of 0.75. Bulgaria, Cyprus, Malta, Slovakia, and Taiwan are missing NTB rates, so the red solid line for these countries only includes tariffs.

Appendix Table 1—Carbon Taxes Implicit in Trade Policy, Sensitivity Analysis

	Global				US Imports			
	Tariffs		NTBs		Tariffs		NTBs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. Main estimates	-32.31***	-11.17**	-89.78***	-75.67**	-5.69***	-6.55***	-47.96***	-37.41***
	(8.59)	(5.52)	(27.33)	(30.02)	(1.44)	(2.30)	(10.06)	(12.36)
Other econometrics								
2. Tobit (no IV)	-35.63***	-5.29	-157.58***	-146.00**	-6.19***	-3.61***	-270.19***	-156.78***
	(11.52)	(6.09)	(40.74)	(59.37)	(1.96)	(1.30)	(60.86)	(56.43)
3. Tobit (IV)	-44.10***	-11.57**	-191.05***	-154.37**	-7.22***	-10.04***	-480.32***	-369.11**
	(15.40)	(5.74)	(56.30)	(70.22)	(2.29)	(3.59)	(132.43)	(158.31)
4. Standard errors	-32.31***	-11.17***	-89.78***	-75.67***	—	—	—	—
clustered by importer	(7.71)	(3.30)	(11.67)	(12.84)	—	—	—	—
Nonlinearity								
5. Logs	-0.65	-0.91**	-0.09***	-0.02	-0.64*	-0.22	-0.07***	-0.04*
	(0.46)	(0.43)	(0.03)	(0.05)	(0.36)	(0.59)	(0.02)	(0.02)
6. Quadratic in emissions								
no IV. CO_2 rate	-58.33***	3.58	-194.52***	-152.31	-10.15**	-1.29	-45.45*	8.17
	(20.32)	(14.81)	(55.98)	(113.86)	(4.65)	(5.63)	(25.49)	(27.49)
CO_2 rate^2	9,539.88**	-3,508.35	34,582.94**	34,420.37	1,260.10	-355.19	1,055.59	-4,798.88
	(4,668.97)	(4,695.02)	(14,405.20)	(34,372.49)	(807.49)	(882.31)	(5,166.68)	(4,704.39)
fitted slope, 10th pct.	-51.56	1.09	-169.99	-127.89	-9.22	-9.22	4.62	4.62
fitted slope, 50th pct.	-46.70	-0.70	-152.35	-110.34	-8.22	-8.22	0.82	0.82
fitted slope, 90th pct.	-30.26	-6.74	-92.77	-51.04	-4.86	-4.86	-11.99	-11.99
7. Nonparametric marginal effect (no IV)	-18.56	—	-81.48	—	-4.89	-4.89	-41.04	-41.04
Other data cleaning and aggregation								
8. Winsorize dependent,	-25.49***	-10.66*	-90.36***	-75.69**	-5.75***	-6.42***	-51.40***	-38.01***
independent variables	(6.60)	(5.39)	(27.73)	(29.95)	(1.62)	(2.29)	(10.45)	(12.69)
9. Include non-manuf.	-32.31***	-9.91	-84.77***	-72.96**	—	—	—	—
industries	(8.59)	(8.96)	(24.07)	(33.21)	—	—	—	—
Weighted		X		X		X		X

(Continued on next page)

Appendix Table 1—Carbon Taxes Implicit in Trade Policy, Sensitivity Analysis (continued)

	Global				US Imports			
	Tariffs		NTBs		Tariffs		NTBs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10. Multiple partners	-37.33**	-11.23*	-82.63**	-75.70**	-6.95***	-6.55***	-55.10***	-37.41***
(i×j×s level data)	(16.49)	(5.84)	(32.19)	(29.63)	(2.10)	(2.29)	(12.34)	(12.34)
11. i×j×s level data	-38.34**	-16.33**	-84.46**	-93.59**	-6.54***	-2.61*	-54.23***	-38.40***
exporter fixed effects	(17.11)	(6.88)	(33.16)	(37.43)	(1.95)	(1.41)	(11.87)	(14.13)
12. Industry-level data	-21.80**	-12.77**	-124.16**	-78.08*	—	—	—	—
(no IV)	(10.38)	(5.14)	(52.71)	(45.14)	—	—	—	—
13. Add intra-national	-5.80***	-11.90***	-60.48**	-81.84***	—	—	—	—
trade	(1.39)	(3.90)	(23.32)	(21.01)	—	—	—	—
<u>Other measures of emissions</u>								
14. Direct emissions	-27.48***	-11.53	-78.33***	-104.70***	-7.52***	-10.35***	-63.34***	-59.13***
	(7.91)	(8.10)	(22.30)	(34.86)	(2.00)	(3.71)	(16.68)	(20.78)
15. Direct emissions	49.89*	-21.03	183.49**	6.37	-1.86	-6.09**	-15.98	-35.63**
	(28.79)	(24.12)	(78.40)	(135.57)	(1.81)	(2.49)	(16.17)	(16.04)
Total emissions	-62.72**	6.55	-212.24***	-76.56	-4.29**	-2.70***	-35.86***	-14.87***
	(26.28)	(16.00)	(70.42)	(100.21)	(1.66)	(0.87)	(9.14)	(4.16)
16. Include all	-16.93***	-6.55**	-46.71***	-41.65**	—	—	—	—
greenhouse gases	(4.48)	(2.56)	(14.34)	(16.95)	—	—	—	—
<u>Consumption emissions from energy-consuming durable goods</u>								
17. Exclude energy-	-35.30***	-16.50**	-98.47***	-113.23**	-9.60***	-17.40***	-60.92***	-66.09***
consuming durables	(9.38)	(7.90)	(29.80)	(47.39)	(2.10)	(6.50)	(14.00)	(23.26)
18. Adjust CO_2 rates:	-32.91***	-12.33**	-91.04***	-83.46**	-6.04***	-8.34**	-50.89***	-47.66***
50% goods, 50% energy	(8.73)	(6.03)	(27.86)	(33.52)	(1.55)	(3.32)	(11.11)	(16.07)
19. Adjust CO_2 rates:	-32.71***	-12.02**	-90.51***	-81.35**	-6.39***	-11.07*	-53.86***	-63.25**
5% goods, 95% energy	(8.69)	(5.90)	(27.69)	(32.39)	(1.67)	(6.29)	(12.31)	(30.48)
<u>Additional sensitivity analyses</u>								
20. Reverse regression	-0.0004***	-0.0002	-0.0006***	-0.0003**	-0.0040***	-0.0040***	-0.0009	-0.0009
(no IV)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0011)	(0.0011)	(0.0006)	(0.0006)
21. Lifecycle tariffs	-7.80**	-5.04	-89.68***	-51.46**	—	—	—	—
	(3.56)	(9.31)	(26.99)	(25.28)	—	—	—	—
Weighted		X		X		X		X

(Continued on next page)

Appendix Table 1—Carbon Taxes Implicit in Trade Policy, Sensitivity Analysis (continued)

	Global				US Imports			
	Tariffs		NTBs		Tariffs		NTBs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
22. No importer fixed effects	-32.05***	-13.51*	-97.58	-83.65***	—	—	—	—
	(8.42)	(7.18)	(55.30)	(30.55)	—	—	—	—
23. WIOD, not Exiobase (no IV)	-13.43	-19.88	-19.54	-121.44	—	—	—	—
	(12.87)	(16.83)	(40.09)	(84.18)	—	—	—	—
24. Add industry fixed effects	28.80	7.48	-16.09	123.97	—	—	—	—
	(25.46)	(15.32)	(13.39)	(85.56)	—	—	—	—
25. Exclude manuf. food, ag. goods	-5.29	-5.87	-75.67**	-40.81**	-5.70***	-6.68***	-36.55***	-37.67***
	(6.09)	(4.52)	(30.02)	(17.36)	(1.47)	(2.33)	(8.87)	(12.22)
Trade war in 2018								
26. U.S. tariffs in 2017	—	—	—	—	-4.80***	-4.14**	—	—
	—	—	—	—	(1.68)	(1.45)	—	—
27. U.S. tariffs including 2018 protectionism	—	—	—	—	-3.97***	-4.29**	—	—
	—	—	—	—	(1.43)	(1.75)	—	—
Weighted		X		X		X		X

Notes: All regressions are instrumental variables estimates, except where otherwise noted. All regressions include a constant. Parentheses show standard errors clustered by industry except in row 4. In columns 3 and 4, hyphens indicate data which are same as row 1 or which are not available for U.S. imports only (e.g., MECS survey does not cover non-manufacturing; WIOD v. Exiobase not relevant for U.S. microdata; all greenhouse gases not separately reported). Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 2—Carbon Taxes Implicit in Cooperative Versus Non-Cooperative Tariffs

	Cooperative		Non-Cooperative	
	(1)	(2)	(3)	(4)
Panel A. U.S. import tariffs				
CO_2 rate	-6.03***	-4.49**	-78.32***	-62.39***
	(1.71)	(1.94)	(12.70)	(23.96)
N	374	374	374	374
Dep. Var. Mean	0.020	0.013	0.324	0.275
Panel B. Japanese import tariffs				
CO_2 rate	-54.72***	-44.70	-46.99**	-9.18
	(16.61)	(27.00)	(19.06)	(13.43)
N	47	47	47	47
Dep. Var. Mean	0.074	0.040	0.072	0.027
Panel C: Chinese import tariffs				
CO_2 rate	5.25	18.91	-60.50	-3.34
	(10.12)	(12.01)	(54.50)	(68.22)
N	47	47	47	47
Dep. Var. Mean	0.088	0.062	0.547	0.397
Weighted		X		X

Notes: U.S. non-cooperative tariffs apply to Cuba and the Democratic People's Republic of Korea. Chinese non-cooperative tariffs apply to Andorra, the Bahamas, Bermuda, Bhutan, the British Virgin Islands, the British Cayman Islands, French Guiana, Palestinian Territory (West Bank and Gaza), Gibraltar, Monserrat, Nauru, Aruba, New Caledonia, Norfolk Island, Palau, Timor-Leste, San Marino, the Seychelles, Western Sahara, and Turks and Caicos Islands. Japanese non-cooperative tariffs apply to Andorra, Equatorial Guinea, Eritrea, the Democratic People's Republic of Korea, Lebanon, and Timor-Leste. Other countries receive cooperative tariff rates from these countries. See Ossa (2014) for further discussion. All regressions include a constant. Standard errors clustered by industry in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 3—Political Economy Variables, Dirty versus Clean Industries

	Global	U.S.
Regression of variable on "Dirty":	(1)	(2)
Panel A: analyzed for all country×industries		
Upstreamness	0.676***	0.756***
	(0.146)	(0.098)
Intra-industry trade	-0.152	0.252**
	(0.093)	(0.105)
Import pen. ratio	0.031	-0.579***
	(0.086)	(0.101)
Labor share	-0.146**	-0.536***
	(0.069)	(0.102)
Mean wage	-0.107	-0.389***
	(0.127)	(0.104)
Panel B: analyzed for U.S. only		
Inverse export supply elasticity	—	-0.141
	—	(0.106)
Output trends, 1972-2002	—	0.026
	—	(0.105)
Import pen. ratio 1997- 2002	—	-0.085
	—	(0.105)
Workers: share with college (%)	—	-0.176*
	—	(0.105)
Four-firm concentration ratio	—	0.084
	—	(0.106)
Mean firm size	—	0.113
	—	(0.106)
Standard deviation of firm size	—	0.030
	—	(0.106)
Capital share	—	0.058
	—	(0.105)

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Appendix Table 3—Political Economy Variables,
Dirty versus Clean Industries (Continued)

Regression of variable on "Dirty":	Global (1)	U.S. (2)
Shipping cost per dollar×kilometer	—	0.697***
	—	(0.100)
Geographic dispersion	—	-0.022
	—	(0.106)
Workers: unionized (%)	—	0.669***
	—	(0.100)
Workers: unemployment	—	-0.063
	—	(0.106)
Local pollution		0.601***
		(0.102)
PAC contributions	—	-0.188*
	—	(0.104)

Notes: Each table entry is the coefficient from a separate regression of the indicated variable on a dummy for whether an observation has above-median total emissions rate and a constant; Column 1 also includes country fixed effects. All variables are measured in z-scores. Regressions are weighted by the value of imports. Standard errors clustered by industry in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 4—Political Economy Explanations for Implicit Carbon Taxes: One at a Time

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All global trade, weighted						
CO_2 rate	-86.60***	6.36	-87.83***	-89.11**	-87.02***	-90.90**
	(33.44)	(40.92)	(33.00)	(35.71)	(33.64)	(37.97)
Panel B. All global trade, instrument for political economy, weighted						
CO_2 rate	-86.60***	49.78	-76.18*	-113.95*	-70.84*	-98.21*
	(33.44)	(52.40)	(43.52)	(63.04)	(38.23)	(55.32)
K-P F Statistic	—	28.9	9.6	3.9	21.7	24.8
Panel C. U.S. imports, weighted						
CO_2 rate	-49.72***	2.74	-51.99***	-47.50***	-49.75***	-54.32***
	(9.90)	(10.19)	(10.54)	(10.32)	(12.19)	(10.45)
Panel D. U.S. imports, direct CO_2 only						
CO_2 rate	-70.12***	-4.75	-71.73***	-61.11***	-48.24***	-95.27***
	(23.88)	(17.20)	(19.84)	(21.21)	(17.80)	(27.15)
Panel E. U.S. imports, direct CO_2 only, unweighted						
CO_2 rate	-65.28***	3.11	-68.47***	-60.83***	-63.07***	-70.97***
	(16.13)	(11.66)	(17.16)	(16.32)	(17.95)	(17.34)
Upstreamness		X				
Intra-industry			X			
Import pen. ratio				X		
Labor share					X	
Mean wage						X

Notes: Dependent variable in all regressions is sum of tariffs and NTBs. Each observation is a country×industry (Panels A and B) or industry (Panels C, D, and E). In Panels A, B, and C, CO_2 rate is the total rate from inverting an input-output table, which is instrumented with the direct CO_2 rate. In panel B only, the political economy variables (upstreamness, intra-industry share, etc.) are instrumented with the mean of each political economy variable in the industry of interest across the 10 smallest other countries. Panels A and B include country fixed effects. All regressions include a constant. Standard errors clustered by industry in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 5—Political Economy Explanations: All Controls Together

	All global trade			U.S. imports	
	IV	IV	Lasso	IV	Lasso
	(1)	(2)	(3)	(4)	(5)
CO_2 rate	-29.237	-29.600	-24.780	-112.754*	-44.065
	(19.444)	(29.641)	(18.726)	(64.063)	(41.779)
Upstreamness	-0.105***	-0.180***	-0.106***	-0.044***	-0.069***
	(0.017)	(0.029)	(0.017)	(0.016)	(0.015)
Intra-industry trade	-0.004	-0.051	0	-0.007	0
	(0.010)	(0.053)	0	(0.015)	0
Import penetration ratio	-0.027**	-0.234***	0	-0.016	0
	(0.012)	(0.072)	0	(0.017)	0
Labor share	-0.012*	-0.360**	0	-0.042	0
	(0.006)	(0.159)	0	(0.026)	0
Workers: mean wage	0.003	0.126	0	-0.034*	0
	(0.019)	(0.078)	0	(0.020)	0
Inverse export supply elast.	—	—	—	-0.023**	0
				(0.011)	0
Output trends 1972-2002	—	—	—	0.007	0
				(0.011)	0
Trend in import pen. ratio	—	—	—	0.026	0
				(0.016)	0
Workers: share w/ college	—	—	—	-0.034	0
				(0.028)	0
Four-firm conc. ratio	—	—	—	-0.059	0
				(0.038)	0
Mean firm size	—	—	—	0.109*	0
				(0.061)	0
Standard dev. of firm size	—	—	—	-0.120*	0
				(0.062)	0
Capital share	—	—	—	0.032	0
				(0.025)	0
Shipping cost per dollar*km	—	—	—	0.034	0.034
				(0.033)	(0.029)
Geographic dispersion	—	—	—	0.083	0
				(0.053)	0
Workers: unemployed	—	—	—	0.001	0
				(0.028)	0
Workers: unionized (%)	—	—	—	0.025	0
				(0.017)	0
Local pollution				0.008	0
				(0.015)	0
PAC contributions	—	—	—	0.028	0
				(0.021)	0
Instrument political economy		X			

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Appendix Table 5—Political Economy Explanations: All Controls Together (Continued)

Notes: Lasso entries of "0" mean the coefficient is exactly zero. CO_2 intensity refers to total intensity from the input-output table. Total CO_2 rate is instrumented with direct CO_2 rate. In column 2, political economy variables are instrumented with their mean in other countries. Columns 1-3 include country fixed effects. Country fixed effects and excluded instrument are not penalized in Lasso estimates. All regressions include a constant. Standard errors clustered by industry in parentheses.

Appendix Table 6—Country Aggregation in General Equilibrium Model

Country	Aggregation
Australia Japan South Korea Taiwan	Pacific Ocean
Austria Belgium Germany France Luxembourg The Netherlands	Western Europe
Bulgaria Czech Republic Estonia Hungary Lithuania Latvia Poland Romania Russia Slovakia Slovenia	Eastern Europe
Brazil Mexico	Latin America
Canada United States	North America
China	China
Cyprus Spain Greece Italy Malta Portugal Turkey	Southern Europe
Denmark Finland United Kingdom Ireland Norway Sweden	Northern Europe
India Indonesia	Indian Ocean
Rest of the World-Asia and Pacific Rest of the World-Europe Rest of the World-Africa Rest of the World-America Rest of the World-Middle East South Africa Switzerland	Rest of the World

Appendix Table 7—Sectors and Trade Elasticities

Sector	Overall	Caliendo & Parro (2011)	Shapiro (2016)	Bagwell et al. (2018)	Giri et al. (2018)
Agriculture, Hunting, Forestry, and Fishing	9.1	9.1	3.3	22.1	—
	(1.1)	(2.0)	(3.6)	(1.3)	—
Coal and Peat Extraction and Related	5.4	13.5	3.5	5.4	—
	(1.0)	(3.7)	(1.3)	(1.7)	—
Petroleum Extraction and Related	13.5	13.5	3.5	22.4	—
	(1.2)	(3.7)	(1.3)	(11.3)	—
Natural Gas Extraction and Related	8.5	13.5	3.5	—	—
	(1.2)	(3.7)	(1.3)	—	—
Other Mining	4.1	13.5	3.5	4.1	—
	(0.7)	(3.7)	(1.3)	(0.9)	—
Food, Beverages, and Tobacco	4.4	2.6	5.3	11.0	3.6
	(0.2)	(0.6)	(2.1)	(1.4)	(0.3)
Textiles, Textile Products, and Leather	6.4	8.1	18.6	4.6	3.7
	(0.2)	(1.3)	(5.6)	(0.9)	(0.2)
Wood; Wood and Cork Products	8.2	11.5	5.9	10.5	4.2
	(1.0)	(2.9)	(2.2)	(3.0)	(1.3)
Pulp and Paper	6.9	16.5	5.8	7.9	3.0
	(0.2)	(2.7)	(3.0)	(2.1)	(0.2)
Coke, Refined Petroleum, and Nuclear Fuel	9.0	64.9	9.0	—	3.9
	(0.5)	(15.6)	(4.0)	—	(0.5)
Chemicals, Fertilizer, and Basic Plastics	3.4	3.1	1.6	8.2	3.8
	(0.2)	(1.8)	(3.0)	(2.6)	(0.2)
Rubber and Plastic Products	3.0	1.7	1.6	9.3	4.3
	(0.5)	(2.2)	(3.0)	(3.6)	(0.5)
Glass, Cement, Other Non-Metallic Minerals	3.4	2.4	1.6	8.3	4.4
	(0.4)	(1.6)	(3.0)	(8.0)	(0.4)
Basic Metals and Fabricated Metal	8.0	5.5	12.9	9.1	6.8
	(0.8)	(1.6)	(8.3)	(2.9)	(1.0)
Machinery N.E.C.	6.2	1.5	10.8	9.2	3.3
	(0.2)	(2.8)	(2.8)	(2.2)	(0.2)
Electrical and Optical Equipment	7.9	8.9	10.8	6.9	3.3
	(0.2)	(0.9)	(2.8)	(3.6)	(0.2)
Transport Equipment	5.7	1.2	6.9	7.0	4.5
	(0.5)	(0.7)	(3.7)	(2.9)	(0.8)
Manufacturing, N.E.C., Recycling	5.3	4.0	12.8	5.3	—
	(0.8)	(1.1)	(4.6)	(1.2)	—
Electricity Generation	6.7	4.0	6.7	10.2	—
	(1.0)	(1.1)	(3.2)	(5.0)	—
All other industries	6.7	4.0	6.7	18.5	—
	(1.0)	(1.1)	(3.2)	(9.5)	—
Land, pipeline, air, and sea transportation	5.3	4.0	6.7	—	—
	(1.0)	(1.1)	(3.2)	—	—

Appendix Table 8—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare, General Equilibrium Model Estimates

	CO_2 Emissions (1)	Real Income (2)	CO_2 Intensity = (1) - (2) (3)	Climate damages (4)	Social welfare (5)
Panel A: Counterfactual sets tariffs and NTBs to mean					
1. Global totals	-1.55%	0.97%	-2.52%	-0.03%	1.00%
2. By region					
Pacific Ocean	7.71%	0.80%	6.91%	—	—
Western Europe	8.21%	1.61%	6.60%	—	—
Eastern Europe	0.58%	1.32%	-0.74%	—	—
Latin America	-8.36%	0.85%	-9.21%	—	—
North America	-6.11%	0.33%	-6.44%	—	—
China	4.07%	0.97%	3.10%	—	—
Southern Europe	24.21%	1.36%	22.85%	—	—
Northern Europe	17.01%	1.72%	15.29%	—	—
Indian Ocean	-1.39%	0.75%	-2.14%	—	—
Rest of World	-5.95%	1.17%	-7.12%	—	—
3. Decomposition					
Scale	0.79%	—	—	—	—
Composition	-0.98%	—	—	—	—
Technique	-1.36%	—	—	—	—
4. By Fossil fuel					
Coal	0.22%	—	—	—	—
Oil	-3.14%	—	—	—	—
Natural gas	-2.92%	—	—	—	—
Panel B: Counterfactual sets EU tariffs and NTBs to mean					
5. Global	-0.72%	0.60%	-1.32%	—	—
6. By region					
Pacific Ocean	-1.12%	0.07%	-1.19%	—	—
Western Europe	9.45%	1.50%	7.95%	—	—
Eastern Europe	0.56%	0.22%	0.34%	—	—
Latin America	-7.04%	0.12%	-7.16%	—	—
North America	-0.58%	0.05%	-0.63%	—	—
China	-0.20%	0.31%	-0.51%	—	—
Southern Europe	25.22%	1.28%	23.94%	—	—
Northern Europe	11.99%	1.58%	10.41%	—	—
Indian Ocean	-1.19%	0.13%	-1.32%	—	—
Rest of World	-2.67%	0.98%	-3.65%	—	—

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Appendix Table 8—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare, General Equilibrium Model Estimates (Continued)

	CO_2 Emissions	Real Income	CO_2 Intensity = (1) - (2)	Climate damages	Social welfare
	(1)	(2)	(3)	(4)	(5)
Panel C: Counterfactual sets tariffs and NTBs to mean of cleanest third of goods					
Global totals	-3.81%	0.38%	-4.18%	-0.08%	0.46%
Panel D: Counterfactual sets tariffs and NTBs to mean of dirtiest third of goods					
Global totals	-2.51%	1.31%	-3.83%	-0.06%	1.37%
Panel E: All countries add a carbon tariff					
Global totals	-0.073%	0.004%	-0.077%	0.00%	0.004%
Panel F: All Countries set tariffs and NTBs to zero					
Global totals	3.39%	2.60%	0.80%	0.08%	2.52%

Notes: Global change in real income refers to the weighted mean percentage change in countries' real incomes due to a counterfactual policy, where weights equal each country's baseline income. In all baseline and counterfactual scenarios, intra-national tariffs and NTBs are assumed to equal zero.

Appendix Table 9—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare, Sensitivity Analysis

	CO_2 Emissions (1)	Real Income (2)	CO_2 Intensity = (1) - (2) (3)	Climate damages (4)	Social welfare (5)
Panel A: Reform All Trade Policy					
1. Baseline estimates	-1.55%	0.97%	-2.52%	0.03%	0.94%
Other data					
2. WIOD, not Exiobase	-0.37%	0.58%	-0.95%	0.02%	0.56%
3. Trade elasticities: Caliendo-Parro	-1.51%	0.82%	-2.32%	-0.08%	0.89%
Other counterfactuals					
4. Harmonize within importer	-0.92%	1.05%	-1.97%	0.03%	1.02%
5. Harmonize tariffs only	-0.77%	0.08%	-0.85%	0.03%	0.05%
6. Harmonize NTBs only	-0.79%	0.85%	-1.64%	0.00%	0.85%
Other estimation methods					
7. First remove trade deficits	-1.61%	0.97%	-2.59%	0.00%	0.97%
8. Algorithm: trust-region	-1.55%	0.97%	-2.52%	0.03%	0.94%
9. Algorithm: Levenberg-Marquardt	-1.55%	0.97%	-2.52%	0.03%	0.94%

Notes: See notes to Table 5. Unless otherwise noted, all estimates refer to changes in both tariffs and NTBs.