ONLINE APPENDIX: THE ENVIRONMENTAL BIAS OF TRADE POLICY

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A Data Details

For most outcomes, I report separate results using U.S. data, primarily for data quality reasons—the U.S. provides a second and independent measure of CO_2 emissions, provides greater industry detail (around 350 NAICS 6-digit industries), reports effective and not just statutory tariff rates, and generally provides higher-quality and better-documented data. The U.S.-only analysis uses U.S. data for both tariffs and CO_2 emissions, and therefore implicitly assumes that emissions rates in other countries are the same as in the U.S. The global analysis does not make this assumption. Online Appendix A.5 describes additional details on data used to measure U.S. CO_2 emissions.

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

[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.

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.

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). Exiobase uses Euros as its base currency; I convert Euros to dollars using the mean annual exchange rate from the IMF's International Financial Statistics and deflate to 2016 dollars using the U.S. GDP deflator. The main Exiobase sample is restricted to observations with non-missing tariffs, NTBs, and CO2 rates.

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:

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

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 (A.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 2009a,b), 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. Environmental Protection Agency (USEPA 2014).

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×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×industry's reported gross output. If a country×industry reports zero output, I set CO_2 emissions for that country×industry also to equal zero. To aid computation, I replace the roughly 2 percent of country×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).

One adjustment is needed to the data to match the quantitative model outlined below. Both Exiobase and WIOD report inventory adjustments for each country×sector, which in some cases are negative. I interpret negative inventory adjustments as output produced in the prior year, then produced and consumed in the current year. I revise total output and bilateral intermediate goods trade to reflect this adjustment (Costinot and Rodriguez-Clare 2014 apply a similar adjustment).

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 Exiobase, 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]

[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.

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×pollutant×county times damages per pollutant×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 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

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.

[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.

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 II, 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)

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. I interpret NTBs as applying to all international trade, including between EU countries (Chen and Novy 2012). The country-by-country map in Figure V 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 anti-dumping 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.

I do not use data on other trade policy instruments since they are not readily available for all countries, though Bond et al. (2019) find some evidence of links between upstreamness and protection using data on export tax equivalents of China's value added tax rebates.

The U.S. tariff data are reported at the level of a 10-digit Harmonized System (HS) code,

and I use a version linked to six-digit North American Industrial Classification System codes (NAICS; see Schott 2008). I calculate U.S. effective import tariff rates as the total duty collected, divided by the cost, insurance, and freight (CIF) value of trade.

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 II, 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 II, 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 (methane and nitrous oxides).

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.

As the main text notes, the U.S. analysis uses U.S. data for both tariffs and CO_2 emissions. This approach relying on the U.S. data is similar to how the Waxman-Markey bill, which passed the U.S. House but not the Senate in 2009, and other U.S. CO_2 cap-and-trade proposals would measure CO_2 emissions for border tax adjustments. Some also argue that measuring CO_2 emissions for a carbon border adjustment from domestic emission rates rather than from the CO_2 content of imports would have a stronger legal basis at the WTO (Staiger 2018). At the same time, this strong assumption of the U.S.-only analysis is important to bear in mind.

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 II, 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.

Measuring CO_2 emissions from an input-output table can involve several pitfalls. One pitfall is that using the average national price of a fossil fuel assumes that all industries face this price. Input-output tables measure expenditures in currency (e.g., dollar) terms, while CO_2 emissions are in physical quantities (metric tons of CO_2). The data on CO_2 emissions use the mean national price of each fossil fuel (e.g., dollars per ton of coal) to translate from currency to quantities. Emission rates (e.g., tons of CO_2 emitted per ton of coal) are then used to translate from quantities of fossil fuels to quantities of CO_2. Bulk discounts, transportation costs, market power, and other forces can make fossil fuel prices differ across industries. Another potential pitfall is that one fossil fuel can vary in its CO_2 intensity—different varieties of coal, for example, have modestly different CO_2 emitted per ton of coal. Additionally, some fossil fuels are physically transformed into products ("feedstocks"), rather than being burned, such as crude oil transformed into plastic. Moreover, input-output tables abstract from heterogeneity within a country×industry—large firms, or firms that export to specific destinations, can have different emissions than the average firm (Lyubich et al. 2018).

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

I address these pitfalls in a few ways. I address heterogeneity in fossil fuel prices and CO_2 rates in part by constructing instrumental variables for CO_2 rates, described below. I address feedstocks by using measures of CO_2 intensity from Exiobase that exclude fossil fuels used for feedstocks. I abstract from heterogeneity in emission rates within a country×industry.

I am not aware of approaches besides the use of input-output tables that can measure emission rates from all industries and countries, and particularly to account for emissions embodied in intermediate goods. National surveys of firms can measure emission rates directly; as described below, I use one such survey for the U.S., and it does not substantially change estimates. The Intergovernmental Panel on Climate Change (IPCC) describes two other approaches to measuring CO_2—"Tier 2" uses country-specific data on emission factors and other variables, and "Tier 3" uses country-specific specialized engineering models and location specific data that are tailored to national circumstances. Because it is country-specific, Tier 3 is difficult to use for comparisons across all countries and industries, and I am not aware of data for all countries and industries using the Tier 2 approach.

An example may clarify what this approach does and does not measure. The emission rate for the vehicle manufacturing industry includes the coal, oil, and natural gas burned to produce the steel, rubber, engine, and assembly of the vehicle, and transportation of the components between the respective manufacturing plants. The emissions rate for vehicle manufacturing does not account for combustion of goods like gasoline that are complements or substitutes for manufactured vehicles. I report sensitivity analyses which adjust the emission rate for energy-consuming durable goods like cars to account for the energy services used to operate them.

A.6 Tariffs On Intermediate Versus Final Goods

I discuss one exercise that may both provide insight on data quality and a public good for research. Some research defines tariffs on intermediate and final goods based on a United Nations Broad Economic Codes (BEC) classification of roughly a dozen broad industry codes into materials, intermediate inputs, and consumer goods (Mishra and Spilimbergo 2011; Amiti et al. 2014; Brandt et al. 2017).

The data in this paper allow an alternative approach. For each source country in Exiobase, I define the third of industries that are most upstream as "intermediate goods" and the third of industries that are least upstream as "final goods." For each destination country (importer), I then calculate the mean tariff on "intermediate goods" and the mean tariff on "final goods." I separately calculate weighted and unweighted averages. An advantage of this approach is that it defines intermediate and final good tariffs based on input-output links between industries, rather than on written industry titles. In case these data are useful for other research, I have posted them, along with the associated BEC averages, online at http://joseph-s-shapiro.com/data.html.

My and the BEC definitions obtain similar mean tariffs—mean weighted tariffs for intermediate goods are 2.3 and 2.6 percent in my and the BEC measures, respectively; and tariffs for final goods are 6.5 and 6.3 percent. My measure has more dispersion – tariffs have a standard deviation of 8.8 versus 7.0 percent – in part since Exiobase allows more detailed industry codes than the BEC, and since the set of which industries are upstream varies slightly across countries in my approach but not in the BEC classification. In a dataset

where each observation is an importer×industry (with two industries, "intermediate" and "final"), a regression of my tariff measure on the BEC measure and a constant obtains a regression coefficient of 0.75 (robust standard error 0.11) in levels or 1.28 (0.11) in logs.

B Econometrics

In equation (1) from the main text, trade policy t is the dependent variable and the emissions rate E is the independent variable, for three reasons: this fits with the theoretical interpretation that an industry's emissions rate is correlated with other political determinants of trade policy; this allows empirical tests of whether the coefficient α represents correlation of CO_2 with omitted political economy variables that determine trade policy; and this allows the coefficient α to be interpreted as the implicit carbon tariff.

Alternatively, one could consider the reverse regression of the emissions rate E on the level of trade policy t. I also show some results using this reverse regression. Trade policy could potentially affect emissions intensities, either through changing import shares (e.g., affecting emissions embodied in intermediate goods) or through affecting productivity (via reallocation, entry, etc.). Some evidence for individual country liberalization episodes suggests that trade liberalization affects plant-level emissions of air or climate change pollution (Martin 2011; Cherniwchan 2017), though I am not aware of any direct evidence on how trade policy systematically affects emissions rates of global bilateral trade flows, which would an interesting subject for for future research.

The instrument is only designed to address attenuation bias due to measurement error. Omitted variables and reverse causality are not problems here because this descriptive analysis estimates the covariance of CO_2 intensity and trade policy within each country, not a causal effect of CO_2 intensity.[7] First-stage regressions and the associated F statistics can test whether this instrument is strong. Because direct emissions constitute a large part of total emissions, this instrument is likely to be strong.

Because this instrument is designed to address measurement error, the main question for validity is whether any measurement error in direct and total emissions is independent. If so, then this instrument can eliminate attenuation bias due to measurement error. If not, then the IV estimates may be biased towards the OLS (i.e., the IV estimates will still suffer from attenuation bias, though less than OLS).

For the U.S. data, this instrument may help correct measurement error since the instrument is built from a separate dataset, MECS, which measures physical fossil fuel consumption separately by industry. Documentation of U.S. input-output tables does not mention MECS (Horowitz and Planting 2006).

In the global data, the instrument still may help address potential measurement error, but because direct and total emissions are measured from the same dataset, the instrument's validity is not certain. Many countries' industrial surveys collect plant-level data on electric-

[7] Since trade policy can change trade volumes, one might wonder whether reverse causality affects the weights X_{ijst} used to calculate E_{js}. This is not a primary concern here for two reasons. First, this does not change the descriptive interpretation of α in equation (1) as the association between trade policy and CO_2 intensity. Second, I report some results at the $i \times j \times s$ level, which do not require averaging over trading partners.

ity and fossil fuel expenditures, which suggests that input-output tables may measure direct emissions with limited measurement error. Usually, these surveys just ask about total expenditures on "materials" without disaggregating by sourcing industry, which suggests they may less accurately measure total emissions. Additionally, energy is typically purchased from a limited number of suppliers (in some countries, state-owned firms), and many countries survey these suppliers. At the same time, the instrument in the global data may not completely eliminate measurement error.

In some settings, using instrumental variables that completely and certainly satisfy the exclusion restriction is central to a paper's arguments. This is not the case here, and my interpretation is that the U.S. instrument is more likely to satisfy the exclusion restriction than the global instrument is. In part the instruments are not critical here because they are solely designed to address measurement error, which is a possible but not a central concern in input-output data. Little if any prior research constructs instruments for an input-output table exclusively out of concern for measurement error. Moreover, in either the global or U.S. analysis, the qualitative conclusions from OLS are similar to those of IV estimates. The main conclusion from this analysis is that measurement error, if anything, means that the true global subsidies in trade policy could even be somewhat larger in absolute value than the large subsidies I estimate.

In equation (1), the destination country fixed effect μ_j implies that this regression compares trade policy across industries within a country. The thought experiment is a country applying similar trade policy on dirty and clean goods. This counterfactual fits the political economy of choosing trade policy, which is made by national authorities. I also show sensitivity analyses without these fixed effects. The idiosyncratic error ϵ contains all unmodeled determinants of import tariff rates.

Equation (1) does not estimate a causal effect of CO_2 intensity on tariffs. Rather, it is a descriptive regression showing the covariance of carbon intensity and trade policy within each country, and so recovers the carbon tariff implicit in trade policy. As discussed earlier, Section 5 develops the interpretation that underlying political economy forces determine tariffs as a function of variables that are omitted from equation (1); these forces are correlated with CO_2 intensity.

Limiting the main analysis to manufacturing makes the global and U.S. data consistent, since the U.S. MECS data are only available for manufacturing, and is consistent with much of the trade literature. The measure of total CO_2 intensity in all these analysis accounts for emissions embodied in intermediate goods from all sectors, not just manufacturing. I report sensitivity analyses that also include other tradable goods (agriculture and mining).

C Implicit Carbon Tariffs: Sensitivity Analyses

Appendix Table I 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, 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.[8] 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.[9] 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 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

[8] 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.

[9] 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.

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 I 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 I, 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 II. 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. Row 28 repeats the estimates of row 27, but controls for each industry's upstreamness. Even in 2018, controlling for upstreamness still eliminates the estimated association between trade policy and CO_2 intensity.

I also separately analyze subsidies to CO_2 implicit in cooperative versus non-cooperative tariffs. Some non-members of the World Trade Organization face higher tariffs not negotiated cooperatively. The tariff data report non-cooperative tariffs for three importers—the U.S., Japan, and China. The U.S. calls these "Column 2" tariffs; China and Japan call them "general rate" tariffs (see Online Appendix A.4).

Appendix Table II shows evidence of implicit carbon subsidies in both cooperative and non-cooperative tariffs. This suggests that whatever political economy force creates these implicit subsidies must operate for both cooperative and non-cooperative policy. The U.S. has a CO_2 subsidy of \$4.50 to \$6/ton in cooperative tariffs and a subsidy of \$60 to \$80/ton in non-cooperative tariffs. Consistent with Figure IV, China does not have a clear implicit subsidy in most of its tariffs. Japanese tariff rates are similar across the two types of tariffs, and correspondingly, the estimated implicit CO_2 subsidy in Japan is generally similar for non-cooperative and cooperative tariffs.

C.1 Political Economy Causes: Sensitivity Analyses

Appendix Table IV shows sensitivity analyses. Panels A, B, and C show that weighted regressions are qualitatively similar to the unweighted versions. Controlling for upstreamness attenuates the global estimated subsidy in trade policy from -\$87 to \$6. The instruments are strong for upstreamness, the labor share, and mean wages. The weighted estimates have weaker instruments for the other explanations, which may bias these estimates towards the OLS values. One might wonder whether the correlation between total CO_2 and upstreamness reflects measurement error in the input-output table, since both upstreamness and total CO_2 emissions are measured from the input-output table. U.S. direct CO_2 emissions are not subject to this concern, since they are measured from completely distinct data (MECS) and not from the input-output table. Panels D and E show that OLS estimates using direct CO_2 emissions are similar to IV estimates for total CO_2 emissions. Controlling for upstreamness in column (2) attenuates the correlation between CO_2 emissions and trade protection by more than 90 percent. Again, controlling for the other political economy variables matters much less.

Appendix Table V reports regressions controlling for all these political economy explanations at once. Columns (1) through (3) show estimates for all global trade. Columns (4) and (5) show estimates for U.S. imports only. The U.S. has data on more political economy explanations. Columns (1), (2) and (4) use linear instrumental variables regression, while columns (3) and (5) use Lasso with instrumental variables (Belloni et al. 2016). All these regressions instrument total CO_2 intensity with direct CO_2 intensity. To ease interpretation of coefficients for the controls, I have re-scaled all except CO_2 intensity to be z-scores (i.e., subtracting the mean and dividing by the standard deviation). I leave CO_2 intensity in tons/\$ rather than z-scores to facilitate comparison with other tables.

These estimates suggest that other political economy forces, and especially upstreamness, account for an important share of the association between CO_2 intensity and trade policy.

These estimates find negative associations between trade policy and CO_2 intensity that are smaller than in estimates without political economy controls. Controls attenuate the association between CO_2 and trade policy to \$-25 to \$-28 and render it statistically insignificant (Appendix Table V).

All the estimates in Appendix Table V identify upstreamness as a strong predictor of trade policy, even conditional on the other political economy variables. Upstreamness is the only explanation for which this is true. Upstreamness also has large magnitude effects on trade policy. In the global data, Lasso retains only the CO_2 rate and upstreamness. In the U.S. data, Lasso retains only three variables in the selected model: CO_2 intensity, upstreamness, and shipping costs.

D 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.[10]

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.[11]

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-

[10] 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.

[11] 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).

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.[12]

E Quantitative General Equilibrium Model

This section resembles the analytical model from the main text, but it allows for many asymmetric countries and industries, specifies the functional form of climate damages, allows for different CO_2 intensity from different industries, allows for deficits, and allows the trade elasticity to vary by industry.

E.1 Model Structure

Assumptions

Preferences are as in equation (5) from the main text. While it is common to assume CES preferences across varieties within a sector and Cobb-Douglas preferences across sectors in a static model, this does impose strong assumptions on the drivers of CO_2 emissions. For example, as mentioned in the introduction, increasing the purchase price of energy-intensive durable good like air conditioners may lead consumers to use existing appliances longer, which is a type of consumption substitution not modeled here. I do report a number of sensitivity analyses involving energy-consuming durable goods specifically, but more broadly, it is important to recognize that the common combination of CES and Cobb-Douglas preferences imposing strong restriction on potential consumption and emissions patterns.

I specify the functional form of climate damages as

$$f(Z) = [1 + \delta(Z - Z_0)]^{-1} \tag{E.1}$$

Here 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 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 in the year 2007, 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 measures damages from emission changes only, since in baseline data, $Z = Z_0$, so the model abstracts from baseline climate damages.

In the data I analyze, shipping represents a separate industry, which is connected through input-output links to other industries (see Appendix Table VII). An alternative approach

[12] 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 2019). This interpretation would argue for direct production subsidies rather than trade policies, and it also would not apply to an undistorted economy already at the first-best.

would be to model shipping and associated emissions directly as a component of trade costs, as in Shapiro (2016). I leave shipping as an industry rather than as a component of trade costs since this approach allows shipping costs to adjust endogenously in the model due to counterfactual policies, since this approach still accounts for oil use different energy intensity of shipping across countries and goods (through the technology summarized in input-output links), and since this lets me directly use the input-output table as reported in data, rather than having to manually adjust it to remove shipping as a component of trade costs but not an industry.

Technology is as in equation (7) from the main text. I include a non-traded sector; one could interpret this as a sector within infinite trade costs.

The pollution emitted to sell goods to a particular destination j are

$$Z_{ijs} = \gamma_{is} \frac{X_{ijs}}{c_{is}(1 + t_{ijs})} \tag{E.2}$$

The coefficient γ_{is} equals the CO_2 intensity of output in country i and sector s. This parameter 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.

Equations (14) and (15) from the main text may help clarify one important channel which the analytical model misses but equation (E.2) captures. Traded goods tend to be more pollution-intensive than domestically purchased goods, both due to long-distance transportation and because trade tends to relocate energy-intensive goods production to countries like China which are relatively pollution intensive. This effect tends to amplify the effect of decreasing energy-intensive exports—not only does the counterfactual make countries emit less to produce goods for export, but a dollar of goods produced for export tends to emit more pollution than a dollar of goods for domestic production.

Exports equal imports minus trade deficits:

$$\sum_{j,s} \frac{X_{ijs}}{1 + t_{ijs}} = \sum_{j,s} \frac{X_{jis}}{1 + t_{jis}} - D_i \tag{E.3}$$

Apart from allowing for deficits, equilibrium is as in the main text.

Baseline Equilibrium

The country×sector price index and unit cost function are as in equations (6) and (7).

The data report the value of bilateral trade in intermediate goods between each pair of origin and destination countries i and j and selling and buying industries s and k, $\tilde{Z}_{ijsk}$. I use the tilde $(\tilde{\cdot})$ to highlight that these raw values from the data exclude tariffs. Data also report final goods trade, indexed by selling but not buying industry, $\tilde{F}_{ijs}$. Define the value of total bilateral trade as $\tilde{X}_{ijs} = \tilde{Z}_{ijs} + \tilde{F}_{ijs}$. Below, I work with tariff-inclusive values of these variables, $X_{ijs} \equiv \tilde{X}_{ijs}(1 + t_{ijs})$, $Z_{ijs} \equiv \tilde{Z}_{ijs}(1 + t_{ijs})$, and $F_{ijs} \equiv \tilde{F}_{ijs}(1 + t_{ijs})$.

Baseline expenditure is similar to the main text but accounts for trade deficits:

$$X_{js} = \beta_{js}(Y_j + D_j + T_j) + \sum_k \alpha_{jsk} R_{jk} \tag{E.4}$$

Substituting tariff revenues $T_j = \sum_{i,s} X_{ijs} t_{ijs}/(1+t_{ijs})$ and the gravity equation (9) into the country×sector expenditure equation (E.4) then simplifying gives the following expression that I use for analyzing counterfactuals:

$$X_{js} = \beta_{js} \left(\frac{Y_j + D_j + \sum_{i,l} \frac{t_{ijl}}{1+t_{ijl}} \lambda_{ijl} \left(\sum_k \alpha_{jlk} R_{jk} \right)}{1 - \sum_{i,l} \frac{t_{ijl}}{1+t_{ijl}} \lambda_{ijl} \beta_{jl}} \right) + \sum_k \alpha_{jsk} R_{jk} \tag{E.5}$$

Several terms here deserve explanation. I measure final good expenditure shares as $\beta_{js} = \sum_i F_{ijs} / \sum_{i,s} F_{ijs}$. Value added in a particular country×sector equals the country×sector revenue minus total intermediate inputs: $Y_{js} = R_{js} - \sum_i Z_{ijs}$. Value-added can also be written as the Cobb-Douglas cost share of factors times country×sector revenue:

$$Y_{js} = (1 - \alpha_{js}) R_{js} \tag{E.6}$$

Deficits equal $D_j = \sum_s D_{js}$, where $D_{js} = \sum_i X_{ijs}/(1+t_{ijs}) - R_{js}$. The intermediate good cost share in country j of industry s in producing goods from industry k is $\alpha_{jsk} = Z_{jsk}/R_{jk}$, where Z_{jsk} is the value of intermediate goods from industry s used to produce goods in industry k and country j. The share of value added from an industry is $y_{js} \equiv Y_{js}/Y_j$. These shares sum to one:

$$\sum_s y_{js} = 1 \tag{E.7}$$

Counterfactual Equilibrium

I rewrite these equations in changes. From equation (7), the cost function is the proportional change in wages and intermediate goods prices, scaled by their Cobb-Douglas expenditure shares:

$$\hat{c}_{is} = \hat{w}_i^{1-\alpha_{is}} \prod_k \hat{P}_{ik}^{\alpha_{iks}} \tag{E.8}$$

The change in trade costs reflects counterfactual tariffs and NTBs:

$$\hat{\phi}_{ijs} = \frac{(1+t'_{ijs})(1+n'_{ijs})}{(1+t_{ijs})(1+n_{ijs})}$$

From equation (E.5), the counterfactual change in expenditure is calculated from

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

Several terms in this equation deserve explanation. Because I use global GDP as the numeraire, this treats baseline trade deficits D_j as a constant share of world GDP in any counterfactual. Counterfactual revenues equal total bilateral sales to foreign and domestic customers:

$$\hat{R}_{is} R_{is} = \sum_j \frac{X'_{ijs}}{1+t'_{ijs}} \tag{E.9}$$

From equation (E.6), counterfactual revenues can be calculated as $\hat{R}_{is}R_{is} = \hat{w}_i\hat{y}_{is}y_{is}Y_i/(1-\alpha_{is})$. From equation (9), bilateral sales can be calculated as $X'_{ijs} = \hat{\lambda}_{ijs}\lambda_{ijs}\hat{X}_{js}X_{js}$. From equation (E.7), counterfactual industry shares are given by

$$\sum_s \hat{y}_{is}y_{is} = 1 \tag{E.10}$$

The numeraire can be expressed as $\sum_i \hat{Y}_i Y_i = 1$.

For baseline data, these equations hold exactly. Under counterfactual tariffs or NTBs, I solve this system to find the values $(\hat{c}_{is}, \hat{y}_{is}, \hat{w}_i)$ that make equations (E.8), (E.9), and (E.10) hold with equality. I use these to find the resulting change in real income, which can be written as

$$\hat{V}_j = \frac{Y_j + \widehat{D_j} + T_j}{\hat{P}_j}$$

From equation (E.2), I calculate the change in pollution and social welfare:

$$\begin{aligned}\hat{Z}_i &= \frac{\sum_s \gamma_{is}\hat{R}_{is}R_{is}/\hat{c}_{is}c_{is}}{\sum_s \gamma_{is}R_{is}/c_{is}} \\ &= \frac{\sum_s (\hat{R}_{is}/\hat{c}_{is})Z_{is}}{\sum_s Z_{is}}\end{aligned}$$

Finally, the change in social welfare is

$$\hat{W}_j = \frac{\hat{V}_j}{[1+\delta(Z'-Z_0)]}$$

E.2 General Decomposition

I first show a single equation including all the channels, and then discuss a diagram that highlights each channel separately. We can write the change in pollution emissions due to a counterfactual trade policy as follows:

$$\hat{Z}_s = \left[\sum_i \frac{\hat{X}^F_{i,s}X^F_{i,s} + \hat{X}^I_{i,s}X^I_{i,s}}{\hat{c}_{i,s}X_{i,s}}\hat{\lambda}_{ii,s}\frac{Z_{ii,s}}{Z_s}\right] + \left[\sum_{i,j\neq i} \frac{\hat{X}^F_{j,s}X^F_{j,s} + \hat{X}^I_{j,s}X^I_{j,s}}{\hat{c}_{i,s}X_{j,s}}\hat{\lambda}_{ij,s}\frac{Z_{ij,s}/(\widehat{1+t_{ijs}})}{Z_s}\right] \tag{E.11}$$

$$\hat{Z} = \frac{\sum_s \hat{Z}_s Z_s}{\sum_s Z_{i,s}} \tag{E.12}$$

Equation (E.11) describes the change in emissions from fossil fuel s (coal, oil, or gas) due to extraction of that fuel in country i. Equation (E.12) shows how the total change in a country's emissions is a weighted sum of changes in emissions across fuels, weighted by baseline emission shares of each fuel. Of course, changing production of other industries affects these three fuels through input-output links, factor prices, and other channels.

Comparing equation (E.11) with equation (14) from the analytical model of the main text shows obvious parallels. Indeed, with two symmetric countries and two industries, and

without separating expenditure into its component on final and intermediate goods, equation (E.11) simplifies to equation (14). The analytical model also discusses a second equation (15) for the change in emissions. While an analogous derivation is straightforward here, with many asymmetric countries the resulting equation is cumbersome and provides less insight.

Appendix Figure IV separates equation (E.11) into several components. This figure describes the equations for coal, but the terms are identical for each fossil fuel. Similarly, I have written out all the terms for domestic coal sales only, but could write out similar terms for coal exports. Each term in this figure represents the proportional change in one channel due to a counterfactual policy. The numbers in parentheses refer to columns in Appendix Table IX.

In Appendix Figure IV, term (1) shows the first breakdown—the change in total emissions from coal can be decomposed into the change in coal that is burned domestically and coal that is exported. This is an exact decomposition because total emissions from coal equal the weighted sum of emissions for domestic sales and exports, weighted by baseline emission shares. These two channels correspond to the two terms in equation (E.11) above.

Terms (2) and (3) of Appendix Figure IV show that the change in emissions due to domestically sold coal combines two channels—one due to the change in coal prices (the "price index channel") and the other due to change in nominal coal sales (the "nominal revenue channel."). This is not an exact decomposition—one cannot take sums or products of these two channels to obtain the exact change in emissions for domestic sales. One could think of this as turning off certain channels in this general equilibrium model, and assessing how the other channels contribute to the result.

Terms (4) through (6) of Appendix Figure IV show that the change in nominal revenues consists of three channels. Term (4) reflects the change in the share of expenditures going to domestic rather than foreign sellers ($\hat{\lambda}_{ii,s}$). Term (5) reflects the direct effect of the change in tariffs ($1/(\widehat{1+t_{ii,s}})$), which change the wedge between consumer spending and firm revenues. Of course, because I assume intra-national tariffs are zero, this channel does not operate for domestic sales, though it does for exports. Term (6) reflects the change in country×sector expenditure ($\hat{X}_{j,s}$). Finally, terms (7) and (8) separate the change in country×sector expenditure into the change in expenditure on final versus intermediate goods.

Appendix Table IX presents the numerical results of this decomposition. This is a decomposition of the effect of each country harmonizing tariffs and NTBs, as in the main text. Each column number in Appendix Table IX corresponds to the term of the same number in Appendix Figure IV. Panels A, B, and C show patterns for oil, natural gas, and coal separately. Column (9) shows total baseline emissions in billions of metric tons CO_2 ($GtCO_2$); these values add up to about 30 billion tons, which is close to published measures of total CO_2 emissions from fossil fuel combustion in the year 2007.

Panel A of Appendix Table IX describes how this counterfactual affects emissions from oil, which account for 37 percent of baseline emissions. Column (1) shows that the counterfactual decreases emissions from exported oil by 8 percent, and decreases emissions of domestically sold oil by 1 percent. This is intuitive—because the counterfactual makes trade policy on energy-intensive goods (including oil) more stringent, emissions from trade in these goods declines. Columns (2) and (3) show that most of the change in emissions from exports

reflect a nominal change in spending on oil, rather than a change in the price of oil. This separation is relevant since emissions reflect the real rather than nominal amount of oil crossing international borders. Column (4) shows that the change in oil exports is primarily due to reallocation of spending between foreign and domestic sources, i.e., $\hat{\lambda}_{ijs}$. Column (5) shows that the direct effect of trade policy is a minority of the total change in the value of international trade in oil. Column (6) shows that the total change in spending on oil is small, and columns (7) and (8) show that it is due about equally to lower spending oil as both a final and intermediate good.

These patterns in Pattern A of Appendix Table IX give a rule of thumb to interpret the large decrease in emissions from oil. Recalling that $\hat{\lambda}_{ijs} = (\hat{c}_{is}\hat{\phi}_{ijs}/\hat{P}_{js})^{-\epsilon_s}$ and noting that the price index channel in column (2) has small magnitude, suggest that the direct effect of changing trade costs, $(\hat{\phi}_{ijs})^{-\epsilon_s}$, accounts for a large share of the change in oil sales.

One might expect this decrease in emissions from internationally traded oil to be offset by an increase in domestic sales of oil, yet Panel A of Appendix Table IX suggests that this does not occur. Why? Two forces do increase emissions of domestically sold oil—column (4) shows that the counterfactual makes domestic purchases represent a larger share of expenditure on oil, and column (7) shows that expenditure on oil as a final good increases slightly, due to the additional tariff revenue the increase in oil tariffs provides. However, other forces outweigh these channels: column (2) shows that the price of oil increases, which decreases the real value of spending on oil and thus emissions from it; and column (8) shows that spending on oil as an intermediate good falls, due in part to the decrease in demand from other energy-intensive industries.

Natural gas has fairly similar patterns to oil, though the magnitudes vary. Emissions from traded natural gas fall by 13 percent, while emissions from domestically sold natural gas fall by 1 percent. The direct effect of tariffs on trade in natural gas accounts for much of this change (column 4). The increase in prices of natural gas tends to decrease emissions (column 2), and changes in emissions from natural gas as a final and intermediate goods somewhat offset each other (columns 7 and 8).

Coal has somewhat different patterns, for a specific reason. India's import tariffs on coal in 2007 were 50 percent, higher than most other Indian import tariffs and higher than import tariffs on coal in other countries. In the years since, India has decreased its import tariffs on coal. Nonetheless, because this counterfactual harmonizes tariffs for each importer across industries, this counterfactual decreases India's tariffs on coal by more than 40 percentage points. This single channel is large enough to increase emissions from internationally traded coal substantially, and decrease emissions from domestically purchased coal. Because trade in coal is only about 10 percent of coal in baseline data, however, the rapid percentage growth in exports has limited effects on total global emissions. The decrease in demand for coal as an intermediate good also substantially decreases global emissions.

E.3 Scale, Composition, and Technique Decomposition

Write global pollution Z as the product of total global output X, the share κ of global output that comes from each industry, and the emissions e per unit output for each industry: $Z = X\kappa' e$. Totally differentiating gives $dZ/Z = dX/X + d\kappa/\kappa + de/e$. The first term on the right-hand side here is the scale effect, the second term is the composition effect, and

the third is the technique effect. While this model has no technical change, this is a global decomposition of country×industry data, so the technique effect in part reflects reallocation of production within an industry across countries with different technologies.

I implement this decomposition as follows. I measure composition as the baseline CO_2 intensity of each industry, weighted by the change in the industry's share of global output:

$$\text{Composition Effect} = \sum_s \left[\frac{\sum_i Z_{is}}{\sum_i R_{is}} \cdot \frac{\sum_i \hat{R}_{is} R_{is} (\hat{P}_{iis})^{-1}}{\sum_{i,s} \hat{R}_{is} R_{is} (\hat{P}_{iis})^{-1}} \right] \left(\frac{\sum_{i,s} Z_{is}}{\sum_{is} R_{is}} \right)^{-1} - 1$$

Here R_{is}, Z_{is}, and P_{is} represent a country×industry's revenue, pollution emissions, and price index, respectively. The first ratio in this expression is the baseline global emissions intensity of industry s. The second ratio is the change in the real global output of this industry, divided by the change in global output of all industries. I multiply these and sum over industries, which provides the change in emissions intensity that would have occurred with observed changes in composition (second ratio) valued at baseline emissions intensities (first ratio). The third ratio is the inverse of the global baseline emissions intensity, so that the composition effect represents a percentage change relative to baseline intensity. I measure the scale effect as the change in real global output:

$$\text{Scale Effect} = \frac{\sum_{i,s} \hat{R}_{is} R_{is} (\hat{P}_{iis})^{-1}}{\sum_{i,s} R_{is}} - 1$$

I measure the technique effect as a residual, equal to the counterfactual change in emissions, minus the scale effect and minus the composition effect:

$$\text{Technique Effect} = \frac{\sum_{i,s} Z'_{is}}{\sum_{i,s} Z_{is}} - 1 - \text{ Scale Effect} - \text{Composition Effect}$$

E.4 Other Counterfactual Results

For the main counterfactual, Panel A of Appendix Table VIII reports sensitivity analyses. I report results using trade elasticities from Caliendo and Parro (2015), allowing for a larger elasticity of substitution of two across the energy sectors (coal, gas, petroleum, and electricity; the elasticity in baseline estimates is assumed to be one due to the baseline Cobb-Douglas functional form); and using two alternative numerical algorithms. Most of these estimates find broadly similar results to the main estimates. The change in global emissions is about equally from tariffs and NTBs.

The main text uses the quantitative model to study one counterfactual, and here I discuss several others. In the second counterfactual, only the EU imposes this policy change: $t'_{ijs} = \sum_s t_{ijs} X_{ijs} / \sum_s X_{ijs}$ $\forall i \neq j; j \in EU$; $t'_{ijs} = t_{ijs}$ $\forall j \notin EU$. Harmonizing EU trade policy between clean and dirty industries may be somewhat politically feasible since the EU has a domestic climate change policy, is concerned about leakage, and supports strong environmental policies.

The third and fourth counterfactuals compare the consequences of changing tariffs and NTBs to the levels of clean versus dirty industries. Specifically, for each country separately,

the third counterfactual increases tariffs to the mean tariff for the cleanest third of industries, and the mean NTB to the mean NTB for the cleanest third of industries. The fourth counterfactual undertakes the same exercise, but for the dirtiest third of industries.

In the fifth counterfactual, all countries add a carbon tariff to existing policy: $t'_{ijs} = T_{ijs} + E_{ijs}d$. Here, E_{ijs} is the emission rate and d is damages chosen to reflect the global externality from CO_2 emissions (\$40/ton). In the sixth counterfactual, all countries set tariffs and NTBs to zero: $t'_{ijs} = 0 \ \forall i, j, s$.

I also investigated a counterfactual which holds trade policies for transportation equipment fixed. This obtains similar results to the main counterfactual—global CO_2 emissions fall 3.8 percent and real income increases 0.7 percent. As emphasized earlier, this model analyzes fossil fuel from production rather than consumption, so the primary policies affecting oil demand in the model are those that affect shipping and that affect heavy-long distance trade which tends to be oil intensive.

Appendix Table VIII presents the results of these other counterfactual analyses. Panel B considers the second counterfactual, in which the EU harmonizes trade policy between clean and dirty goods. The effects of the EU policy resemble those of the global policy from Table V, but the magnitudes are smaller. This counterfactual EU policy would decrease global CO_2 emissions by 1.8 percentage points while increasing global real income by 0.3 percentage points. Although global emissions fall, most of the increase in emissions is from within the EU, which reflects the idea that the subsidies in trade policy this paper highlights are global—low baseline EU tariffs and NTBs on dirty goods increases emissions from outside the EU, and hence increasing those tariffs and NTBs tends to increase emissions from inside the EU (though produce larger decreases from outside the EU).

Appendix Table VIII, Panels C and D, show the effects of harmonizing trade policy to the levels of clean versus dirty goods. Both counterfactuals decrease global CO_2 emissions, by 2.5 to 3.8 percent. Real income increases slightly in both counterfactuals, so global CO_2 intensity falls by 4 percent. These counterfactuals suggest that harmonizing trade policy between clean and dirty goods can decrease global CO_2 emissions, regardless of whether the counterfactual trade policy is changed to the level that clean or dirty goods initially face.

Appendix Table IX, Panel E, considers a counterfactual in which all countries impose a carbon tariff, i.e., increase existing tariffs by the marginal damage of CO_2 emissions embodied in trade policy and leave NTBs unchanged. This decreases global emissions by 2.5 percent.

Appendix Table VIII, Panel F, eliminates import tariffs and NTBs. This policy reform increases real income by 2.6 percent, which is large enough to cause an increase in global CO_2 emissions. Here, the scale effect dominates any other effects of this policy on CO_2 emissions.

Why do some counterfactuals increase real income but decrease global CO_2 emissions? This happens because these reforms address two market failures—trade policy and global CO_2 emissions. Eliminating or harmonizing trade policy across goods can increase real income. Because trade policy encourages consumption and production of dirty goods, eliminating this price signal also decreases consumption and production of those dirty goods.

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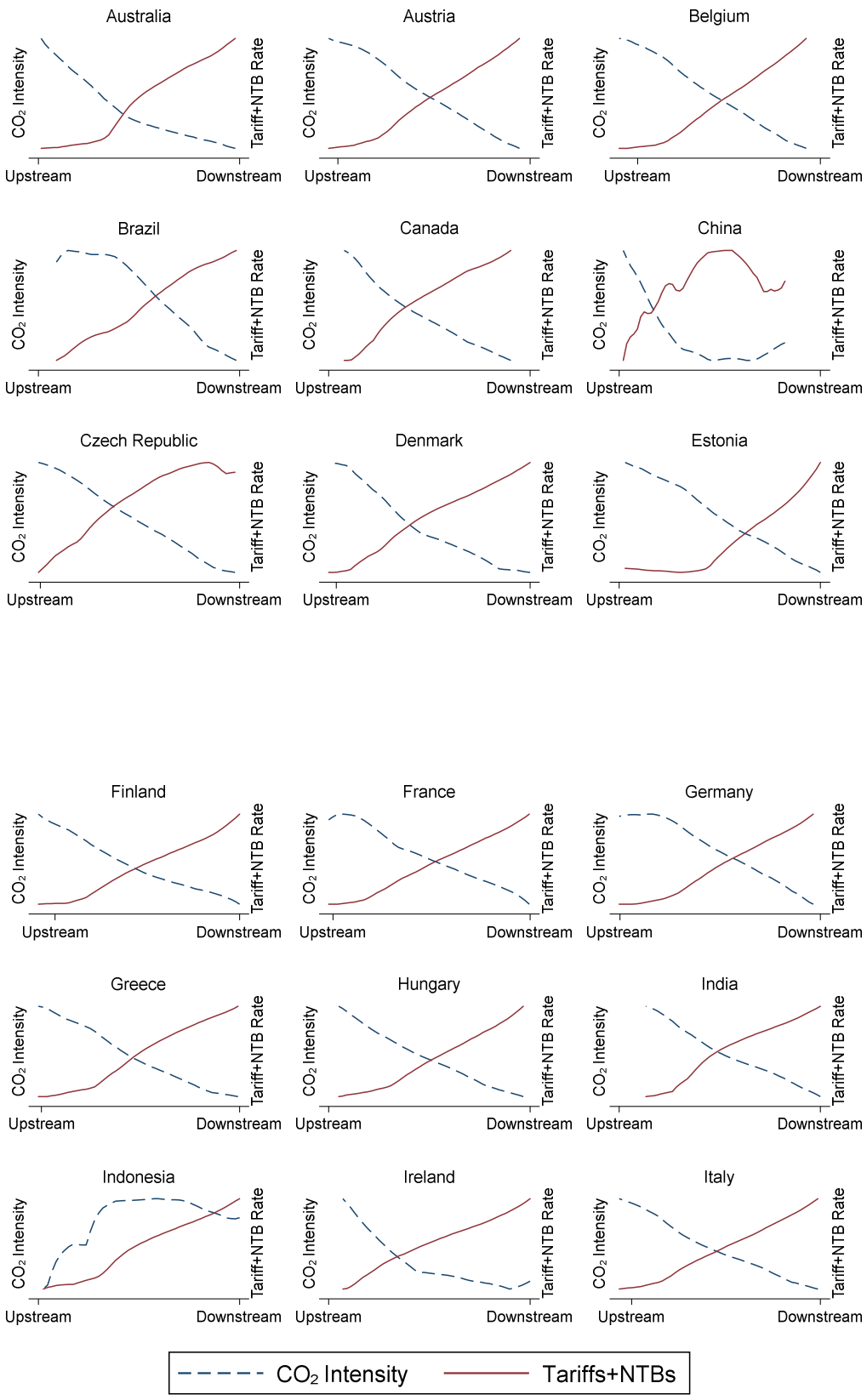
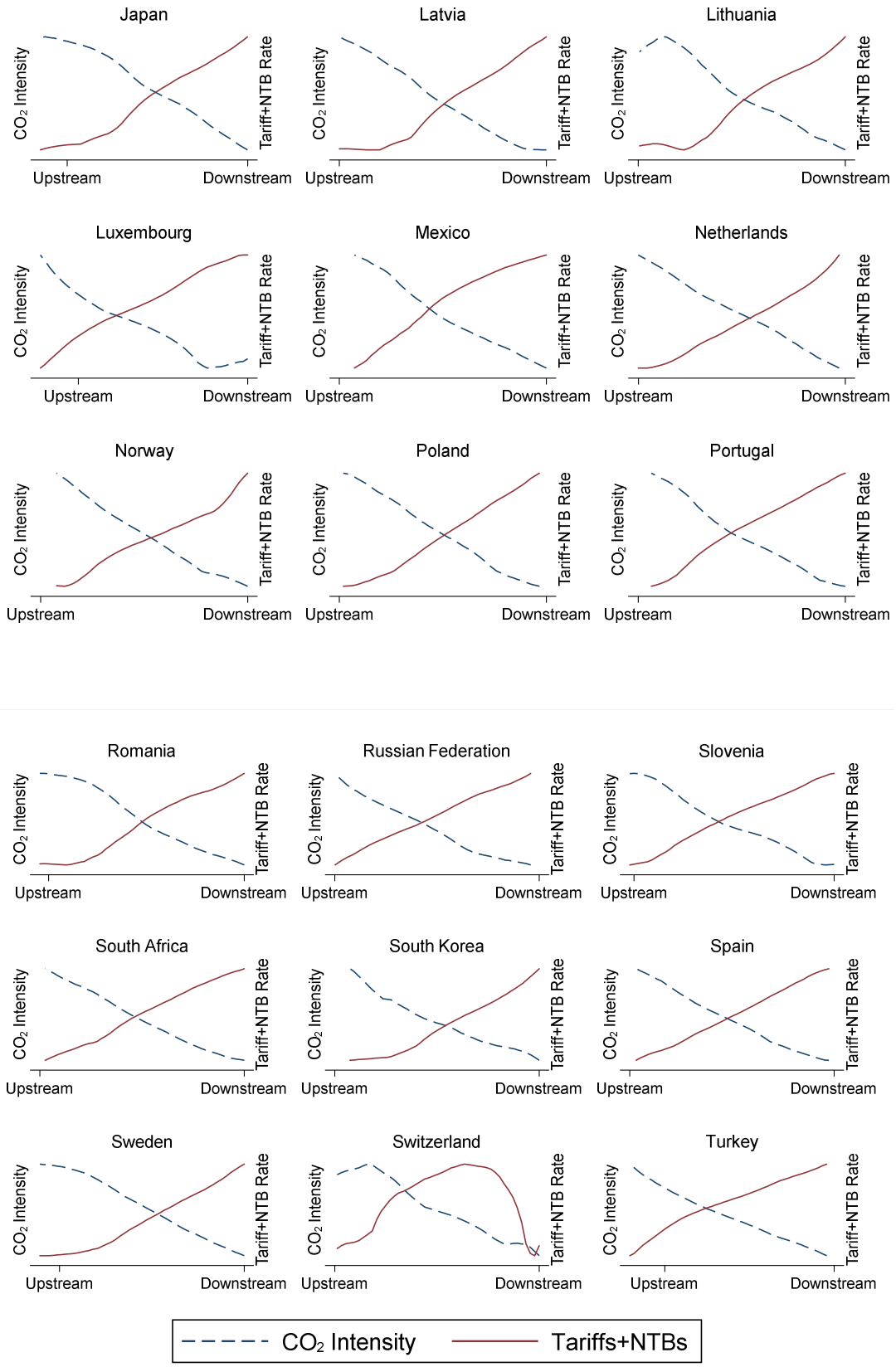
APPENDIX FIGURE I

Upstream Location, CO_2 Intensity, and Trade Policy, by Country



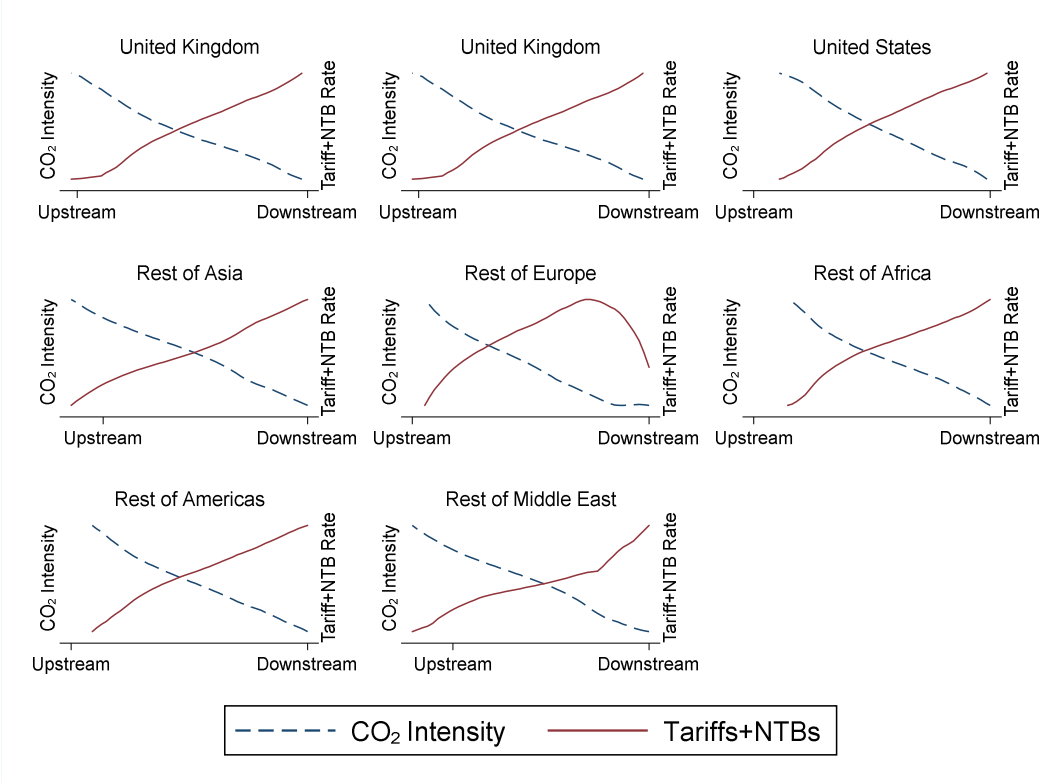
APPENDIX FIGURE I

Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)



APPENDIX FIGURE I

Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)

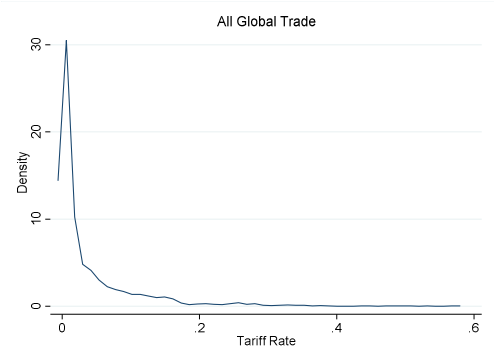


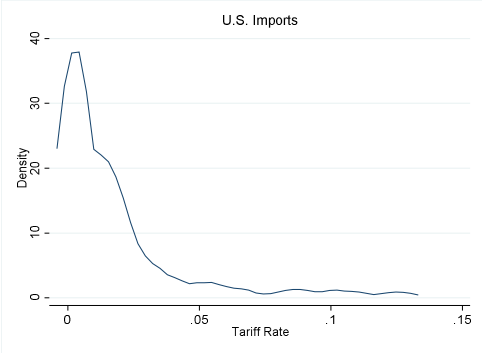
Notes: In each graph, the solid red line is from a local linear regression of import tariffs on the industry's upstreamness. The dashed blue line is from a local linear regression of CO_2 intensity on the industry's upstreamness. Upstreamness is the simple measure of the share of an industry's output 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 FIGURE II

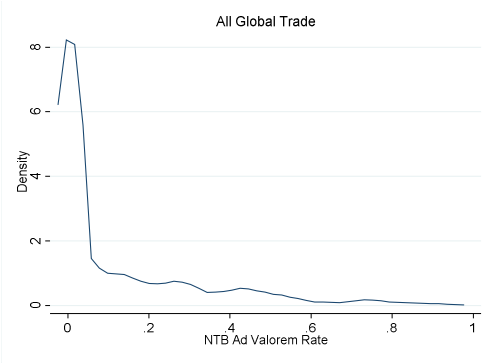
Densities of Trade Policy, Carbon Intensity, and Upstreamness

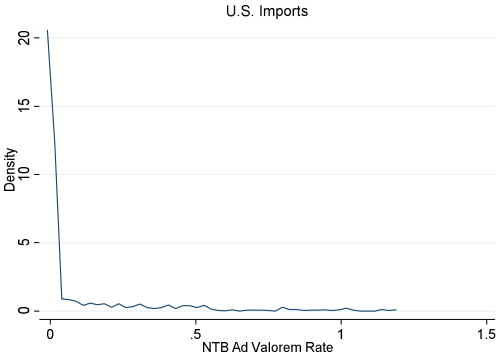
Panel A. Density of tariffs



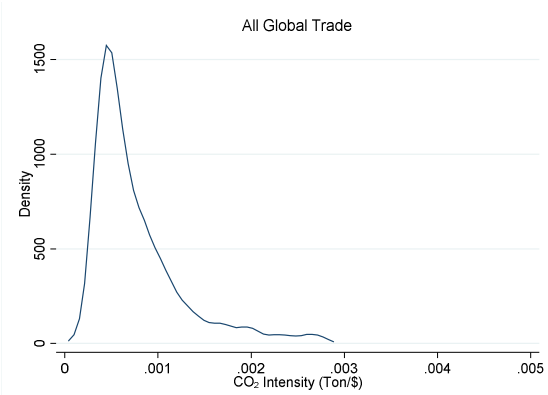


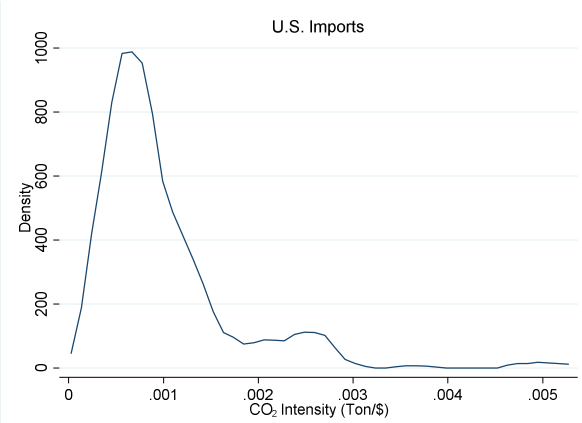
Panel B. Density of non-tariff barriers





Panel C. Density of Total CO_2 intensity





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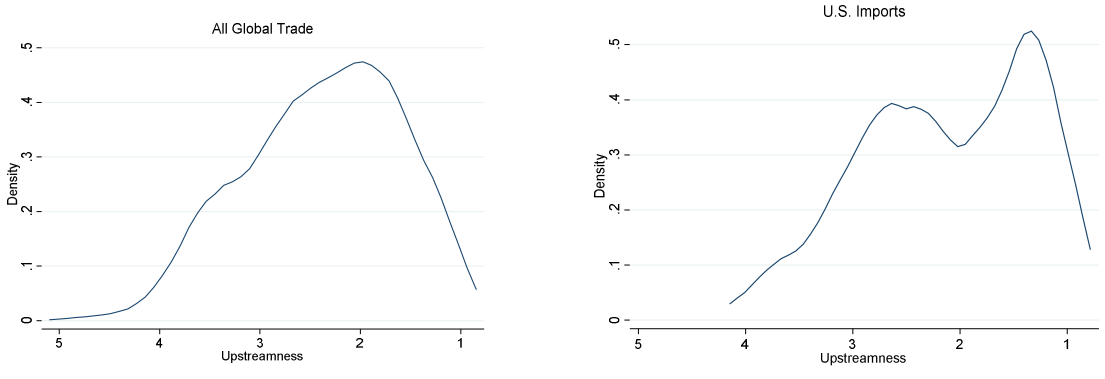
APPENDIX FIGURE II

Densities of Trade Policy, Carbon Intensity, and Upstreamness (Continued)

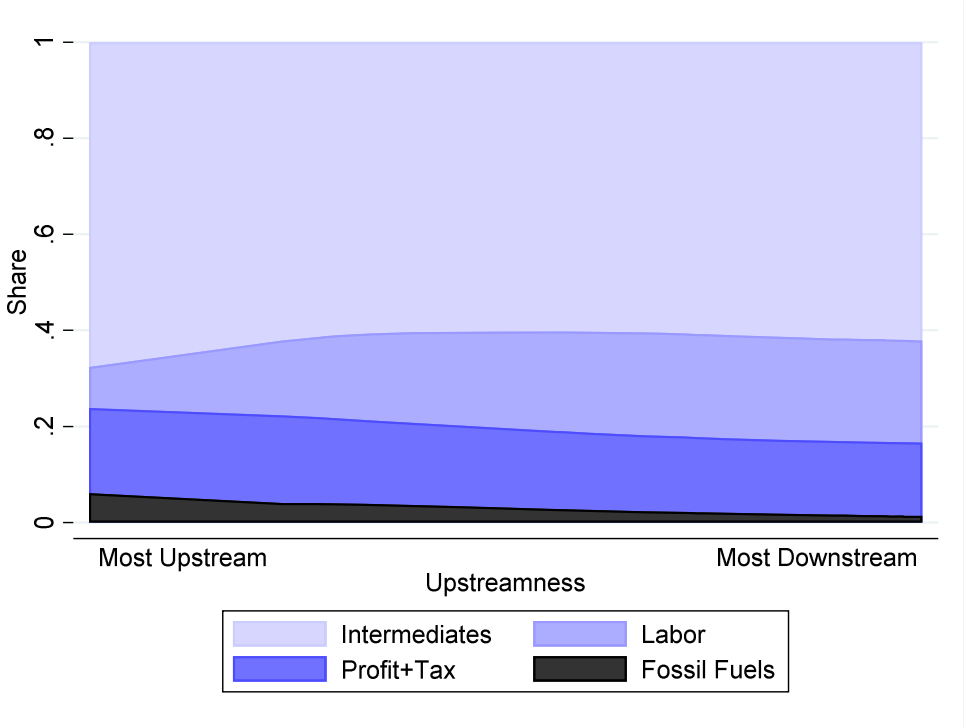
Panel D. Density of upstreamness



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 III

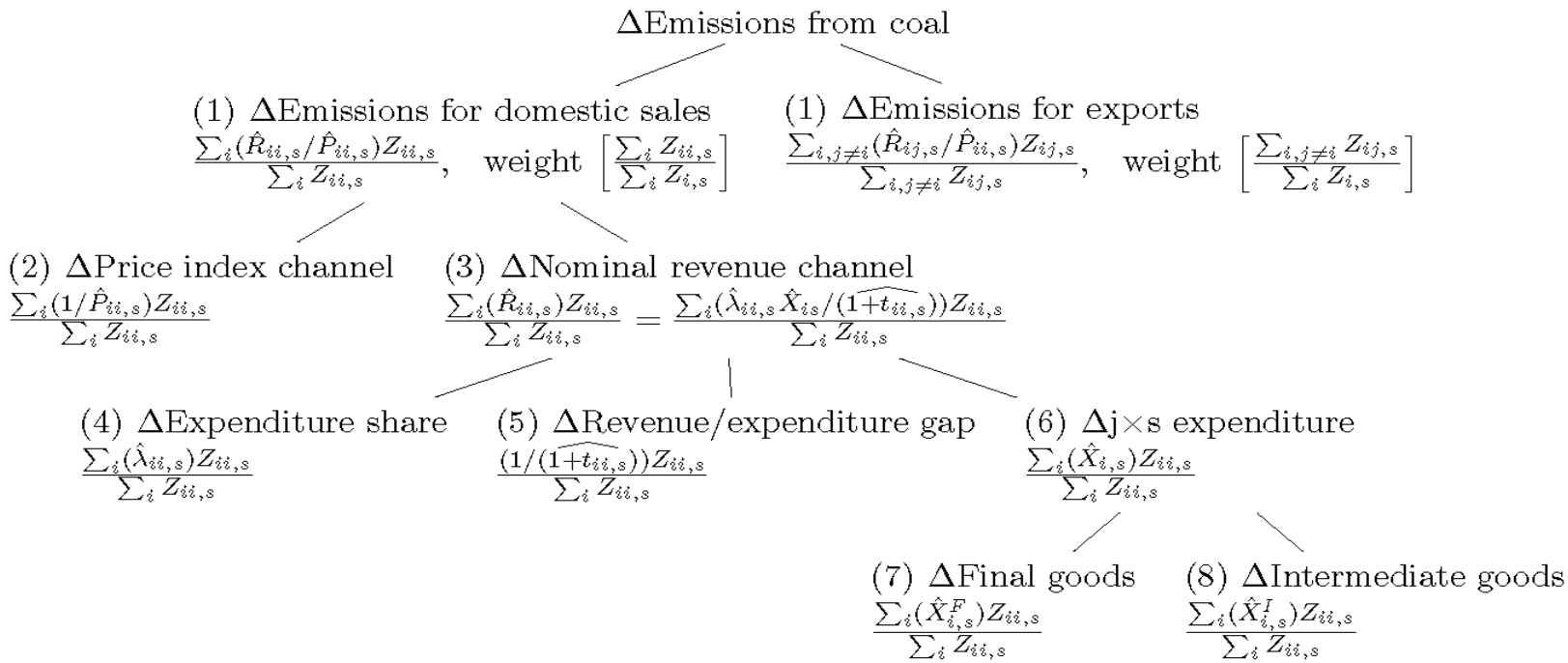
U.S. Upstreamness and Components of Revenues



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 IV

Decomposition of Quantiative Model



Notes: Equation numbers correspond to columns in Appendix Table IX. The Δ symbols indicate that each channel represents the proportional change due to a counterfactual policy.

APPENDIX TABLE I

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	-1.55	-44.67	4.62
fitted slope, 50th pct.	-46.70	-0.70	-152.35	-110.34	-8.22	-1.84	-43.84	0.82
fitted slope, 90th pct.	-30.26	-6.74	-92.77	-51.04	-4.86	-2.78	-41.02	-11.99
7. Nonparametric	-18.56	—	-81.48	—	-4.89	-4.89	-41.04	-41.04
marginal effect (no IV)								
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 I

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)	—	—	—	—
Other measures of emissions								
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)	—	—	—	—
Consumption emissions from energy-consuming durable goods								
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)
Additional sensitivity analyses								
20. Reverse regression	-0.0004***	-0.0002	-0.0006***	-0.0003**	-0.0040***	-0.0063	-0.0003**	-0.0009
(no IV)	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0011)	(0.0040)	(0.0001)	(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 I

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	-32.05***	-13.51*	-99.99	-83.65***	—	—	—	—
effects	(8.42)	(7.18)	(57.69)	(30.55)	—	—	—	—
23. WIOD, not Exiobase	-11.62	-18.64	-19.54	-126.03	—	—	—	—
(no IV)	(12.47)	(18.57)	(40.09)	(92.67)	—	—	—	—
24. Add industry fixed	28.80	7.48	-16.09	123.97	—	—	—	—
effects	(25.46)	(15.32)	(13.39)	(85.56)	—	—	—	—
25. Exclude manuf.	-5.29	-5.87	-75.67**	-40.81**	-5.70***	-6.68***	-36.55***	-37.67***
food, ag. goods	(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	—	—	—	—	-3.97***	-4.29**	—	—
2018 protectionism	—	—	—	—	(1.43)	(1.75)	—	—
28. U.S. tariffs in 2018,	—	—	—	—	0.62	-0.18	—	—
ctrl. for upstreamness	—	—	—	—	(1.57)	(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. Hyphens indicate data which are same as row 1 or which are not available (e.g., MECS survey does not cover non-manufacturing; WIOD versus Exiobase is not relevant for U.S. microdata; all greenhouse gases are not separately reported for these U.S. data). Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

APPENDIX TABLE II

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 III

Political Economy Variables, Dirty versus Clean Industries

Regression of variable on "Dirty":	Global (1)	U.S. (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 III
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 IV

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 V
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 V

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 VI
Country Aggregation in General Equilibrium Model

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

APPENDIX TABLE VII
Sectors and Trade Elasticities

Sector	Overall	Caliendo & Parro (2015)	Shapiro (2016)	Bagwell et al. (2018)	Giri et al. (2018)
Agriculture, Hunting, Forestry, and Fishing	9.11	9.11	3.34	22.13	—
	(1.05)	(2.01)	(3.63)	(1.31)	—
Coal and Peat Extraction and Related	5.38	13.53	3.45	5.38	—
	(0.97)	(3.67)	(1.27)	(1.65)	—
Petroleum Extraction and Related	13.53	13.53	3.45	22.38	—
	(1.20)	(3.67)	(1.27)	(11.31)	—
Natural Gas Extraction and Related	8.49	13.53	3.45	—	—
	(1.20)	(3.67)	(1.27)	—	—
Other Mining	4.13	13.53	3.45	4.13	—
	(0.73)	(3.67)	(1.27)	(0.92)	—
Food, Beverages, and Tobacco	4.42	2.62	5.26	11.01	3.57
	(0.24)	(0.61)	(2.10)	(1.42)	(0.27)
Textiles, Textile Products, and Leather	6.36	8.10	18.56	4.62	3.71
	(0.16)	(1.28)	(5.59)	(0.90)	(0.16)
Wood; Wood and Cork Products	8.19	11.50	5.90	10.47	4.17
	(0.97)	(2.87)	(2.23)	(3.00)	(1.26)
Pulp and Paper	6.85	16.52	5.77	7.93	2.97
	(0.18)	(2.65)	(3.00)	(2.06)	(0.18)
Coke, Refined Petroleum, and Nuclear Fuel	8.95	64.85	8.95	—	3.87
	(0.47)	(15.61)	(4.01)	—	(0.47)
Chemicals, Fertilizer, and Basic Plastics	3.44	3.13	1.55	8.15	3.75
	(0.22)	(1.78)	(3.04)	(2.57)	(0.22)
Rubber and Plastic Products	2.99	1.67	1.55	9.25	4.31
	(0.48)	(2.23)	(3.04)	(3.58)	(0.50)
Glass, Cement, Other Non-Metallic Minerals	3.43	2.41	1.55	8.31	4.44
	(0.37)	(1.60)	(3.04)	(8.00)	(0.38)
Basic Metals and Fabricated Metal	7.99	5.45	12.94	9.13	6.84
	(0.84)	(1.62)	(8.35)	(2.87)	(1.05)
Machinery N.E.C.	6.23	1.45	10.84	9.18	3.27
	(0.21)	(2.80)	(2.84)	(2.19)	(0.21)
Electrical and Optical Equipment	7.92	8.93	10.84	6.91	3.27
	(0.20)	(0.93)	(2.84)	(3.63)	(0.21)
Transport Equipment	5.68	1.23	6.88	6.98	4.47
	(0.51)	(0.70)	(3.66)	(2.88)	(0.80)
Manufacturing, N.E.C., Recycling	5.25	3.98	12.76	5.25	—
	(0.78)	(1.08)	(4.57)	(1.16)	—
Electricity Generation	6.69	3.98	6.69	10.23	—
	(1.00)	(1.08)	(3.17)	(4.99)	—
Services and all other industries	6.69	3.98	6.69	18.45	—
	(1.02)	(1.08)	(3.17)	(9.45)	—
Land, pipeline, air, and sea transportation	5.34	3.98	6.69	—	—
	(1.02)	(1.08)	(3.17)	—	—

APPENDIX TABLE VIII

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 benefits (4)	Social welfare (5)
Panel A: Sensitivity Analysis for Main Counterfactual					
1. Baseline estimates	-3.59%	0.65%	-4.24%	0.08%	0.57%
2. Trade elasticities: Caliendo-Parro	-5.66%	0.55%	-6.21%	0.13%	0.42%
3. Larger energy elasticity	-2.53%	0.47%	-3.00%	0.06%	0.41%
3. Harmonize tariffs only	-1.75%	0.13%	-1.88%	0.04%	0.09%
4. Harmonize NTBs only	-2.26%	0.47%	-2.73%	0.05%	0.42%
5. Algorithm: trust-region	-3.59%	0.65%	-4.24%	0.08%	0.57%
6. Algorithm: Levenberg-Marquardt	-3.59%	0.65%	-4.24%	0.08%	0.57%
Panel B: Counterfactual sets EU tariffs and NTBs to mean					
Global total	-1.84%	0.25%	-2.10%	—	—
By region					
Pacific Ocean	-1.63%	0.06%	-1.69%	—	—
Western Europe	20.35%	0.82%	19.53%	—	—
Eastern Europe	1.50%	0.12%	1.38%	—	—
Latin America	-4.65%	0.01%	-4.66%	—	—
North America	-0.12%	0.01%	-0.13%	—	—
China	-0.97%	0.00%	-0.97%	—	—
Southern Europe	50.43%	0.58%	49.85%	—	—
Northern Europe	17.04%	0.96%	16.08%	—	—
Indian Ocean	-1.98%	-0.17%	-1.81%	—	—
Rest of World	-7.51%	0.04%	-7.55%	—	—
Panel C: Counterfactual sets tariffs and NTBs to mean of cleanest third of goods					
Global total	-5.09%	0.06%	-5.15%	0.11%	-0.05%
Panel D: Counterfactual sets tariffs and NTBs to mean of dirtiest third of goods					
Global total	-4.20%	1.13%	-5.33%	0.09%	1.04%
Panel E: All countries add a carbon tariff					
Global total	-2.52%	0.45%	-2.97%	0.06%	0.39%
Panel F: All Countries set tariffs and NTBs to zero					
Global total	1.31%	2.65%	-1.34%	-0.03%	2.68%

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

Components of Changes in Fossil Fuel Consumption Due to Counterfactual Trade Policy

	Total	Prices	Nominal Revenue						Baseline Emissions	Counterfactual Emissions
						Country×Sector Expenditure				
			Total	Expenditure Share	Revenue / Expenditure	Total	Final Goods	Intermediates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Oil										
Domestic Sales	-1.2%	-0.3%	-1.0%	1.3%	0.0%	-0.7%	0.6%	-0.7%	5.7	5.7
Exports	-8.2%	-0.6%	-6.4%	-7.5%	-1.5%	-0.8%	-0.7%	-0.7%	5.7	5.2
Panel B: Natural Gas										
Domestic Sales	-0.9%	-0.5%	-0.5%	0.0%	0.0%	-0.5%	0.6%	-0.6%	4.4	4.3
Exports	-12.8%	-0.5%	-11.0%	-11.6%	-1.5%	0.7%	-0.6%	0.8%	1.5	1.3
Panel C: Coal										
Domestic Sales	-4.7%	0.5%	-5.2%	-3.2%	0.0%	-2.1%	-0.5%	-2.1%	12.6	12.0
Exports	9.1%	0.3%	8.0%	8.0%	-1.1%	1.0%	-0.5%	1.1%	1.2	1.4

Notes: Emissions refer to 2007 baseline emissions in $GtCO_2$. See text for definitions of each column in terms of the model.