The Environmental Bias of Trade Policy*

Joseph S. Shapiro
UC Berkeley and NBER
joseph.shapiro@berkeley.edu

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Abstract

This paper documents a new fact, then analyzes its causes and consequences: in most countries, import tariffs and non-tariff barriers are substantially lower on dirty than on clean industries, where an industry's "dirtiness" is defined as its carbon dioxide (CO_2) emissions per dollar of output. This difference in trade policy creates a global implicit subsidy to CO_2 emissions in internationally traded goods and so contributes to climate change. This global implicit subsidy to CO_2 emissions totals several hundred billion dollars annually. The greater protection of downstream industries, which are relatively clean, substantially accounts for this pattern. The downstream pattern can be explained by theories where industries lobby for low tariffs on their inputs but final consumers are poorly organized. A quantitative general equilibrium model suggests that if countries applied similar trade policies to clean and dirty goods, global CO_2 emissions would decrease by several percent annually, and global real income would not change.

JEL: Q50, Q56, F6, F13, F18, H23

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1 Introduction

This paper documents a new fact, then analyzes its causes and consequences: in most countries, import tariffs and non-tariff barriers (NTBs) are substantially lower on dirty than on clean industries, where an industry's "dirtiness" is measured by its carbon dioxide (CO_2) emissions per dollar of output. This difference between dirty and clean industries creates an implicit subsidy to CO_2 emissions in internationally traded goods and so contributes to climate change. I describe this pattern as trade policy's environmental bias.

This bias is widespread. I find it in essentially all countries, in both tariffs and NTBs, in both cooperative and non-cooperative tariffs, in all years with data, and regardless of whether weighted by the value of trade flows. I find some evidence that these patterns have attenuated over time, though they remain large. The implicit subsidy I estimate, of around \$90 per ton of CO_2, is interesting because the global social cost of CO_2 emissions (and hence the optimal tax on CO_2 emissions) is usually estimated as around \$40 per ton of CO_2 (IWG 2016). The magnitude of the environmental bias of trade policy is therefore larger than what research suggests is an optimal tax on CO_2 emissions, and the sign is opposite—trade policy is imposing lower tax rates on dirtier goods, while an optimal carbon policy would impose higher tax rates on dirtier goods.

One way to interpret this fact is in terms of climate change policy. Optimal climate change policy would impose a uniform Pigouvian tax (or equivalent quantity mechanism like a cap-and-trade market) in all countries and industries, since CO_2 creates the same climate change externality regardless of where it is emitted. Researchers and policymakers often claim that imposing climate change policy in some countries but not others could harm domestic energy-intensive industries and lead to relocation or "leakage" of emissions, more than an absolute decrease in emissions. Climate change regulation is far from global and covers about 20 percent of global CO_2 emissions, including in the EU, California, New England, British Columbia (Canada), and elsewhere (World Bank 2018). Carbon prices in these policies differ substantially across regulations and are generally below \$10/ton. Some countries have considered pairing such sub-global policy with an import tariff or border adjustment that is proportional to the CO_2 emitted from producing and transporting goods.[1]

Of course, most countries already impose tariffs and NTBs on traded goods. This paper asks whether dirty industries already face higher tariffs and NTBs, which would mean that countries already implicitly have a carbon tariff in their existing trade policies. Ex ante, one might expect dirtier industries to receive relatively greater trade protection, since dirty industries lobby heavily, and industries invest in lobbying

[1]Some versions of this proposal would include rebates for exports. Several proposed U.S. climate change regulations would implement such carbon tariffs or carbon border adjustments, including the Waxman-Markey Bill (the American Clean Energy and Security Act), which passed the House but not the Senate in 2009; the American Opportunity Carbon Fee Act of 2014; and a current "carbon dividends" proposal by the U.S. Climate Leadership Council led by James Baker, Martin Feldstein, Greg Mankiw, and publicly endorsed by 27 economics Nobel laureates and 3500 economists. One common perception is that a carbon border adjustment is politically necessary (though so far not politically sufficient) to ensure support for any U.S. climate change regulation. Legal analyses suggest that regulations of the World Trade Organization (WTO) could allow such carbon tariffs, though disagree on exactly which type of carbon tariff WTO rules would allow (Hillman 2013; Pauwelyn 2013; Cosbey et al. 2017).

in part to obtain protection from foreign competition.[2] The results show that this ex ante intuition is incorrect, and that dirtier industries face relatively lower tariffs and NTBs than clean industries do.

I obtain these findings from regressions of tariff (or ad valorem NTB) rates on CO_2 intensity. I measure CO_2 intensity by inverting a global multi-region input-output table, which accounts for emissions embodied in intermediate goods. For example, the CO_2 emissions rate for U.S. kitchenware accounts for the Australian coal used to produce the Chinese steel used to produce a U.S. frying pan, and the bunker and diesel fuels used to transport each. These measures of CO_2 intensity differ for each unique combination of origin country, destination country, origin industry, and destination industry. The global input-output data this paper uses, from Exiobase, describe 48 countries and 163 industries, and so generate roughly 60 million ($\approx 48^2 \times 163^2$) measures of CO_2 intensity with a separate measure for each international and intra-national trade flow in the global economy. Some of the Heckscher-Ohlin literature calculates the factor content of trade (e.g., Trefler 1993); I essentially use a similar approach to calculate the coal, oil, and natural gas content of trade, and then convert this fossil fuel combustion to CO_2 emissions. The tariff data are even more detailed, with 200 million different tariff measures that uniquely describe each origin×destination×industry. I obtain qualitatively similar results from several sensitivity analyses, including using only U.S. data from the Bureau of Economic Analysis, global data from the World Input Output Database (WIOD), including all industries or restricting to manufacturing industries, or including greenhouses gases besides CO_2.

These findings lead to a natural question: why have countries imposed more protection on clean than dirty industries? Theory and evidence suggest that countries do not explicitly consider CO_2 or intend to subsidize it in choosing trade policy; indeed, I believe that countries are not even aware of the subsidy this paper highlights, since previous literature has not tested for or identified it. Instead, this paper proposes that some forces which determine trade policy are correlated with CO_2 intensity.

To determine which economic forces account for the association between trade policy and CO_2 intensity, the analysis casts a broad net and considers explanations based on nearly 20 different variables suggested by theoretical and empirical research. These explanations include optimal tariffs (inverse export supply elasticities), lobbying expenditures, unionization, labor and capital shares, declining or "sunset" industries, worker wages and education, firm size, industry concentration rates, intra-industry trade, levels and trend in trade exposure, an industry's upstream location, and others. These detailed variables are available for the U.S.; a subset is available for all countries. To address the potential endogeneity of these explanations, some specifications instrument a particular political economy explanation (e.g., mean wages in a specific industry) with its value from other countries. I discuss though do not find support for explanations based on production efficiency (Diamond and Mirrlees 1971).

Among these potential explanations, linear regressions and a machine learning algorithm (the least absolute shrinkage and selection operator, or Lasso) highlight an industry's location or "upstreamness" in global value chains as accounting for a large share of the association between CO_2 intensity and trade pol-

[2] One could generate other ex ante predictions. Dirtier industries generally have higher transportation costs, greater fixed costs, different levels of environmental regulation, and differ in other ways from cleaner industries (Ederington and Minier 2003; Ederington et al. 2005). These other differences could affect the level of trade protection that dirty industries receive.

icy. The analysis measures upstreamness as the economic distance of each industry from final consumers (Antràs et al. 2012). Upstreamness is strongly correlated with CO_2 intensity, and compared to more upstream industries, downstream industries have both greater protection and lower emissions. I show empirically that upstream industries disproportionately use fossil fuels as a direct input to production, whereas downstream industries use greater shares of relatively clean factors of production (e.g., labor).

One could conjecture various forces to explain why upstream industries face lower tariffs and NTBs. While a complete analysis of political economy explanations for the covariance of upstreamness and trade policy is beyond the scope of this paper, I do investigate one possible explanation involving lobbying competition. Firms may lobby for high tariffs and NTBs on their own outputs, but also lobby for low tariffs on their inputs, so as to decrease production costs.[3] Because final consumers are poorly organized (Olson 1965), politicians give the least protection to the upstream industries (which are also the dirtiest) and the greatest protection to the most downstream industries (which are also the cleanest). I discuss the potential roles of CO_2 emissions and upstream production relationships in several theories of trade policy and then quantitatively analyze their importance in one framework, Grossman and Helpman (1994)'s "Protection for Sale." These analyses fit with the interpretation that trade policy superficially suggests that governments care about CO_2 emissions because CO_2 is strongly correlated with upstreamness, but that ultimately upstreamness rather than CO_2 emissions best accounts for existing patterns of trade policy.

A partial equilibrium back-of-the-envelope calculation suggests that this global subsidy to CO_2 emissions totals \$210 to \$580 billion dollars per year. This can be interpreted as revenue that a carbon tariff would collect if it had the same pattern as trade policy's environmental bias (i.e., -\$90/ton). The paper then uses a quantitative general equilibrium trade model to analyze how counterfactual trade policy reforms would affect CO_2 emissions and social welfare. I combine a range of features used in recent models: multiple industries and countries; input-output links; CO_2 emissions from fossil fuels; tariffs that are lump-sum rebated; and NTBs (Costinot and Rodriguez-Clare 2014; Caliendo and Parro 2015; Eaton et al. 2016; Shapiro 2016; Caron and Fally 2018). I separate results based on several market structure assumptions: perfect competition (Eaton and Kortum 2002), monopolistic competition with homogeneous firms (Krugman 1980), and monopolistic competition with heterogeneous firms (Melitz 2003). These frameworks use strong assumptions that make it possible to estimate the effects of specific counterfactual trade policies on CO_2 and social welfare, though of course these assumptions provide a very imperfect approximation of reality.

I use this quantitative trade model to study three counterfactual policies. In the first counterfactual,

[3]Firms publicly emphasize this rationale. When President Trump initially proposed tariffs on steel, the American Automotive Policy Council announced, "The auto industry and the U.S. workers that the industry employs would be adversely affected and that [*sic*] this unintended negative impact would exceed the benefit provided to the steel industry" (Gibson 2017). The Consuming Industries Trade Action Coalition (CITAC), a twenty-year old U.S. lobby group focused on decreasing tariffs on upstream industries, experienced a doubling of membership during a "Stand up to Steel" campaign, and supported a bill in the U.S. House of Representatives (HR 2770) to give steel consumers greater standing in trade cases. When President Obama imposed tariffs on Chinese tires, CITAC responded, "[W]e believe that this case will undermine the jobs of many more US workers in downstream industries..." (Business Wire 2009).

each country sets a single tariff per trading partner which applies to all industries, and which equals the country's mean baseline bilateral tariff. Each country implements a similar reform for NTBs. This turns off bilateral differences in trade policy between clean and dirty goods. I find that this counterfactual would decrease global CO_2 emissions by up to five percent while leaving global real income unchanged or slightly increased. This counterfactual has similar magnitude effects on CO_2 as two of the world's largest actual or proposed climate change policies, the EU Emissions Trading System and the U.S. Waxman-Markey Bill.

In the second counterfactual I consider, only the EU adopts this policy. One could think of this as a way for the EU to address leakage from its CO_2 cap-and-trade market, the EU Emissions Trading System. I find that this second counterfactual would decrease global CO_2 emissions by up to 2 percent and would again leave global real income unchanged or slightly higher. Finally, if countries completely eliminated tariffs and NTBs, CO_2 emissions would fall but global real income would rise. These reforms decrease global CO_2 emissions while increasing global real income because existing trade policy affects two market imperfections: a trade policy barrier to market integration and an environmental externality.

This paper has important policy implications. In a first-best setting where every country implemented uniform carbon prices on all CO_2 emissions, trade policy would have no role in efficient climate policy. In a second-best setting where political economy constraints make optimal climate change policy infeasible, considering environmental concerns in designing trade policy could potentially increase welfare. But in either the first or second best setting, a trade policy which subsidizes CO_2 may be inefficient, and hence limiting the greater protection of clean relative to dirty goods could increase welfare. I believe this type of policy reform, which considers the CO_2 intensity of an industry in negotiating bilateral or multilateral trade policy across industries but without a formal carbon tariff, has not been discussed in government or academia.[4] Such reforms may appeal to groups that typically disagree – dirty industries and environmentalists – because they can maintain protection of dirty domestic industries (at least relative to clean industries) while decreasing global CO_2 emissions. More broadly, an important goal of the World Trade Organization (WTO) has been to decrease protection of downstream relative to upstream industries, since such trade policy reforms would let developing countries sell more advanced technologies to industrialized countries. This paper suggests that such WTO goals may also help address climate change.

Several caveats are worth noting. This paper refers to the higher tariff and NTB rates on clean relative to dirty goods as an implicit "subsidy" to CO_2 emissions. This "subsidy" refers to a lower tax rate in a setting where most goods face positive taxes (tariffs and NTBs). This difference in trade policy may encourage countries to purchase more clean goods domestically and dirty goods from abroad; internationally traded goods within an industry are more CO_2-intensive both because they require long-distance transportation and because they tend to be outsourced to countries like China and India that

[4]Such reforms are likely feasible within WTO regulations. The WTO does not primarily regulate NTBs, so most changes in NTBs are permissible. WTO members negotiate maximum ("binding") tariffs on trading partners. The binding tariffs do constrain the maximum possible level, but WTO members have flexibility in choosing tariffs below those levels through bilateral or multilateral agreements.

rely heavily on coal for production and so are CO_2-intensive (Shapiro 2016). The difference in trade policy also encourages firms and final consumers to substitute from consuming cleaner to dirtier goods (e.g., substituting from aluminum to steel). More broadly, imposing higher tax rates on clean than on dirty traded goods sends a price signal to all agents in the economy that encourages a range of optimizing responses. A quantitative model which describes some of these responses provides one way to understand the myriad effects of this trade policy; Section 6 presents results of such a model. In part since that analysis finds that the difference in trade policy between clean and dirty industries increases global CO_2 emissions, I refer to this difference in trade policy as a "subsidy."

It is also worth discussing the implications of using a second-best tool like trade policy as an alternative or complement to traditional environmental taxes on production or consumption. Important debates have considered the merits of taxing pollution through trade policy (e.g., Kortum and Weisbach 2016). One point of this paper is that current trade policy is subsidizing pollution for political economy (not efficiency) reasons, which no theoretical or empirical arguments claim is efficient.

This paper builds on several literatures. I believe this paper is the first to report the association of tariffs or NTBs with the pollution emitted to produce different goods, and the first to quantify the environmental consequences of harmonizing trade policy between clean and dirty goods. Research on trade and the environment asks how hypothetical changes in aggregate trade flows affect pollution, studies hypothetical carbon tariffs, or investigates how environmental policies and attributes of industries affect trade flows though not trade policies (Antweiler 1996; Copeland and Taylor 2003; Frankel and Rose 2005; Fowlie et al. 2016; Shapiro and Walker 2018). A large literature studies the consequences of hypothetical carbon border tax adjustments, relying primarily on computable general equilibrium (CGE) models and largely or completely abstracting from existing patterns of tariffs or NTBs. An entire field of academia, industrial ecology, quantifies the pollution required to produce internationally traded goods.[5] Unlike this work, I study how actual current levels of tariffs and NTBs relate to pollution emissions. The finding that most countries, years, and trade policy instruments have greater protection for clean than for dirty goods is also novel.

This paper also introduces tariffs and NTBs as a new and important setting to study political economy and the environment. Research on the political economy of environmental policy is limited, though an older theoretical literature studies the political economy of regulation, and some empirical papers relate individual legislator votes to campaign contributions and incidence (Brett and Keen 2000; Oates and Portney 2003) or study rent-seeking in environmental permit allocation (Joskow and Schmalensee 1998). A few theoretical papers use trade policy frameworks like Grossman and Helpman (1994)'s "Protection for Sale" model to study domestic environmental policy (Hillman and Ursprung 1994; Fredriksson 1997;

[5]Industrial ecology has departments, Ph.D. programs, and journals, primarily in Europe. Numerous papers in industrial ecology and some in economics measure pollution embodied in traded goods, a literature sometimes described as consumption-based accounting of CO_2 or other pollution emissions (e.g., Antweiler 1996; Davis and Caldeira 2010; Peters et al. 2011; Aichele and Felbermayr 2012; Steinberger et al. 2012; Feng et al. 2013; Grether and Mathys 2013). None of this work compares its measures of pollution embodied in traded goods against tariffs or NTBs. Since pollution is an externality, once pollution from specific traded goods is measured, it is natural to ask how similar current tariffs on these goods are to their external costs, which is one of this paper's goals.

Schleich 1999; Schleich and Orden 2000). Trade policy provides an appealing setting to study political economy and the environment because it governs the more than 20 percent of global goods that are traded internationally, substantially affects pollution, creates easily-observed tax rates that vary across industries and countries, and depends on political economy forces like lobbying. The political economy of environmental policy is important in general because economists can often describe first-best environmental policy and show that existing policy is far from it, but political economy can help explain why many existing environmental policies are inefficient.

This paper also builds on the trade policy literature by providing the first nonparametric evidence of "tariff escalation" – the phenomenon that more processed goods face higher tariffs – using continuous measures of upstreamness; the first evidence of NTB escalation, which is important since NTBs create a larger trade barrier than tariffs in industrialized countries; and the first empirical link between tariff escalation and the environment. The most relevant parts of the trade policy literature propose general models of trade policy design (Grossman and Helpman 1994, 1995; Maggi and Rodríguez-Clare 1998, 2007), link trade policy to global value chains (Antràs and Staiger 2012; Blanchard et al. 2016), and link trade policy to other domains like the environment (Copeland 2000; Ederington and Minier 2003; Horstmann et al. 2005; Ederington 2010; Maggi 2016).[6] The fact that more processed goods face higher tariffs, sometimes described as "tariff escalation," was a focus of research a half-century ago, when Corden (1966, p. 228) in the Journal of Political Economy described tariff escalation as "so well known that detailed substantiation is hardly needed." Since that time, analysis of tariff escalation has become uncommon in trade policy research, despite renewed interest in global value chains. Most of the literature on tariff escalation lists mean tariff rates for 2-3 groups of goods like "primary," "intermediate," and "consumer goods" (Balassa 1965; UNCTAD 1968; Golub and Finger 1979; Marvel and Ray 1983; Greenaway and Milner 2003). Some work gives the political economy explanation for tariff escalation that upstream industries may lobby for low tariffs on their intermediate inputs (Cadot et al. 2004; Gawande et al. 2012).[7]

The rest of the paper proceeds as follows. Section 2 describes the data. Section 3 explains the econometrics. Section 4 discusses the relationship between pollution intensity and trade policy. Section 5 evaluates political economy explanations. Section 6 evaluates consequences of counterfactual reforms. Section 7 concludes.

[6]Much of the global value chain literature uses the World Input Output Database (WIOD) and related multi-region input-output tables. I focus on a global multi-region input-output table that I believe has not been used in this literature, Exiobase, 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). Appendix tables report qualitatively similar results with WIOD (Timmer et al. 2015).

[7]A few papers mention informally or provide qualitative case studies suggesting that tariff escalation could harm the environment by accelerating invasive species damages or otherwise increasing extraction of exhaustible natural resources, since raw materials may create more environmental damages than processed industries (Hecht 1997; Tu et al. 2008). None compares data on trade policy to environmental data. One suggestive piece of evidence does precede this paper: in one paper defining upstreamness (Antràs et al. 2012), the most upstream manufacturing industries in the U.S. include petrochemicals, copper smelting, and secondary aluminum smelting; these are also some of the dirtiest manufacturing industries.

2 Data

I combine data on three types of variables: trade policy, pollution emissions, and political economy. Unless otherwise noted, all data represent a cross-section for the year 2007 (which is the year Exiobase covers) or the closest available year. Figure 2 shows some estimates with multiple years of U.S. data. Appendix A.1 discusses industry concordances.

2.1 Trade Policy

Tariffs are the most easily-quantified trade policy instrument, but NTBs are increasing in importance.[8] I obtain data on tariff rates from the Market Access Map (Macmap) database. A 2-digit Harmonized System (HS) code version of these data is freely available online. I purchased the 6-digit HS code version from the French *Centre d'Etudes Prospectives et d'Informations* (CEPII) (Guimbard et al. 2012). The data provide the most comprehensive tariff records available from any source. The roughly 200 million tariff observations distinguish 5,000 different goods (6-digit Harmonized System codes) for 190 countries and account for most-favored nation tariffs, regional trade agreements, free trade agreements, customs unions, and tariff-rate quotas. The data cover all bilateral trading partners.[9]

For tariffs on U.S. imports, I use records from the Census Bureau's Imports of Merchandise files. While Macmap lists statutory tariff rates (i.e., official policy), Census records list tariff duties actually paid, so permit calculation of effective tariff rates. As the many types of tariffs in the Macmap database illustrate, accurately interpreting tariff schedules and their exemptions is complex and can introduce measurement error; observing statutory tariffs, as in the U.S., avoids this complexity. The U.S. 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.

Appendix Figure 1, Panel A, plots the density of tariffs, excluding the top 1% for visual clarity. The mean global tariff is around ten percent (0.10), while the 99th percentile globally is sixty percent. U.S. import tariffs are lower, with mean and median around two percent (0.02) and the 99th percentile at nearly fifteen percent.

Non-tariff barriers (NTBs) include policy barriers to trade that are not tariffs, such as price regulations, product standards, quantity restrictions like quotas, or others.[10] I use data from Kee et al. (2009) on the dollar (i.e., ad valorem) equivalent of NTBs; they describe how they calculate these values from raw

[8] I abstract from other trade policy instruments since data on them is not widely available.

[9] The United Nations publishes raw tariff schedules in the Trade Analysis Information System (TRAINS). Macmap uses TRAINS but takes many steps to refine it, such as determining which tariff schedules apply for every good and country pair.

[10] A global social planner would likely set tariff rates to zero, since tariffs largely exist for political economy or terms-of-trade reasons. A global planner might set some NTBs to non-zero rates, since some NTBs could address market failures in health, safety, or the environment. I abstract from efficiency rationales for NTBs in part since I am not aware of data distinguishing the extent to which each country and industry's NTBs are efficient versus reflect rent-seeking and protectionism. It is generally believed that NTB rates have risen in recent decades partly in response to decreased tariff rates, which may suggest that NTBs primarily represent protection rather than correction of market failures.

data in the World Bank's World Integrated Trade Solutions (WITS) system. These NTB values are calculated for each 6-digit HS code, for a year around 2000-2003 (the exact year varies across countries), and for about 100 countries. 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.[11] I interpret these NTBs as applying to all international trade, including between EU countries (Chen and Novy 2012). Appendix Figure 1, Panel B, plots the density of NTBs. For all global trade, tariffs and NTBs have somewhat similar values; for U.S. imports, average NTBs exceed average tariffs.

2.2 CO_2 Emissions

I first explain my approach to measuring CO_2 emissions informally for one closed economy, then explain it formally, then discuss multiple open countries, and finally describe data sources.

Consider two types of CO_2 emissions. First, an industry burns fossil fuels to produce output. Second, an industry purchases intermediate goods as inputs that themselves require CO_2 emissions to produce. I describe the first channel as "direct" CO_2 emissions and the second as "indirect." An input-output table for one country contains one row per industry and one column per industry. Each value in the table represents the dollars of output from an industry in a row required to produce a dollar of output of the industry indicated in a column. This permits calculation of direct CO_2 emissions, since it shows how many dollars of coal, oil, and natural gas are required to produce a dollar of output in each other industry. To calculate direct CO_2 emissions, I consider the rows for to the coal extraction, oil extraction, and natural gas extraction industries. The analysis uses independent data on the national price per physical unit of each fossil fuel and on the physical emissions rate (i.e., the tons of CO_2 emitted per ton of coal, barrel of oil, or cubic foot of natural gas burned). Multiplying these coal, oil, and gas input expenditures by the tons of CO_2 emitted per dollar of fossil fuel burned gives the direct emissions rate. This approach to using an input-output matrix to account for pollution is standard (Miller and Blair 2009, p. 447) and resembles what the Intergovernmental Panel on Climate Change calls the "Tier 1" or "default" method of calculating CO_2 emissions.

This approach can calculate direct but not indirect emissions. For example, the emissions rate for cookware in this approach reflects fossil fuels burned to shape steel into a pan (which are listed in the cookware industry) but not fossil fuels used to make the steel in the first place (which are listed in the steel industry or its input industries like electricity). As shown formally below, inverting the input-output matrix permits calculation of total emissions, which equal the sum of direct and indirect emissions. This inverse indicates the dollars of coal, oil, and natural gas required to produce a dollar of output in each industry, including the coal, oil, and natural gas embodied in intermediate goods, and inputs to intermediates, and inputs to these inputs, etc. This is sometimes called a "life cycle" measure of emissions.

[11] Most NTBs in the raw WITS data apply to all trading partners.

Continuing this explanation for a single closed economy, let S denote the number of industries in the economy and let A be an $S \times S$ input-output table where each row lists the industry supplying inputs and each column lists the industry demanding outputs. Each entry in the matrix A describes the dollars of input from the industry in a given row required to produce a dollar of output for the industry in a given column. Let x be an $S \times 1$ column vector describing each industry's gross output, and let d be an $S \times 1$ vector of final demand, including exports. An accounting identity states that each industry's gross output equals the value of its output used for intermediate goods in all industries plus the value of its output used for final demand: $x = Ax + d$.[12] Simple algebra then reveals the total amount of intermediate inputs (including both direct and indirect inputs) required to produce a dollar of final demand: $x = (I - A)^{-1}d$. The matrix $(I - A)^{-1}$ is called the Leontief inverse or the matrix of total requirements. It describes the dollars of each input, including those required to produce intermediate inputs, and inputs to inputs, etc. required to produce an additional dollar of final demand.

I apply this approach to calculate emissions rates for a dollar of final demand in each industry. I focus on CO_2 from fossil fuel combustion since it accounts for most greenhouse gas emissions and uses the most accurate methods. A sensitivity analysis obtains qualitatively similar results from the additional main greenhouse gases (methane and nitrous oxide), in addition to emissions from processes that are not fossil fuel combustion. This approach does not account for changes in CO_2 emissions from goods that are complementary with or substitutes for the good of interest, which may be most relevant for energy-consuming durable goods like vehicles or housing.

Extending this approach to multiple open countries and industries is straightforward. Let N denote the number of countries. In a multi-region input-output table, A is an $NS \times NS$ matrix, where each row is a specific country$\times$industry and each column is a specific country$\times$industry. For example, one table entry might show the dollars of Chinese steel (one row) required to produce a dollar of U.S. cookware (one column). Then x and d are $NS \times 1$ column vectors describing gross output and final demand, respectively. The rest of the analysis with a multi-region input-output table proceeds as above.

Two examples 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. A second example is the refined petroleum manufacturing industry, which produces gasoline. The emission rate for this industry accounts for all the fossil fuels used as inputs, including those which are physically transformed into gasoline and diesel. This emission rate includes CO_2 from coal burned to heat crude oil at the refinery and CO_2 emitted from a vehicle when the vehicle burns gasoline.

Several data sources help measure CO_2 emissions. The main dataset is Exiobase, which combines trade

[12] Final demand includes final consumption expenditure by households and governments and similar uses of goods. This identity essentially says that a firm's output can either be used for final demand or as an intermediate good, i.e., as an input into another firm's production.

data, input-output tables, and national accounts to construct a global multi-region input-output table.[13] Exiobase reports the direct CO_2 emissions per million Euros of output for every country×industry. To construct data on CO_2 emissions per country×industry, Exiobase primarily uses emissions data from the International Energy Agency (IEA 2007a,b,c). I use Exiobase's calculated CO_2 emissions from fossil fuel combustion for each industry. 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.

I report separate results using U.S. data since the U.S. provides a second and independent measure of CO_2 emissions. The U.S. also provides greater industry detail (around 350 NAICS 6-digit industries). The U.S. analysis uses only U.S. data for both tariffs and CO_2 emissions.[14] 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. Because MECS is limited to manufacturing, this paper's main analysis focuses on manufacturing; sensitivity analyses in appendix tables obtain qualitatively similar results from including all tradable industries. 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. 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 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.

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

[13] I use Exiobase (specifically, version 2.2.2, industry-by-industry, fixed product sales assumption) because it distinguishes 48 countries and 163 industries (Tukker et al. 2013; Wood et al. 2015), 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. Aggregate measures of consumption-based CO_2 accounts (sometimes called a country's "carbon footprint") for most countries differ by less than 10 percent between these various databases (Moran and Wood 2014).

[14] The global analysis measures the CO_2 content of a country's imports according to the CO_2 emissions from the producing country×industry, for the roughly 50 manufacturing industries in Exiobase. Because the U.S. analysis uses entirely U.S. data, it measures the CO_2 content of U.S. imports according to U.S. CO_2 emissions from an industry, for the roughly 350 manufacturing industries in U.S. data. This U.S. approach is more 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 have measured 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).

2.3 Political Economy Explanations

Theories

Why do different industries face different trade policies, or any trade policy at all? One explanation involves optimal tariffs and the terms of trade—a large country can privately benefit by imposing small import tariffs on its trading partners. In this classic explanation, a country's privately optimal tariff equals the inverse of the foreign export supply elasticity it faces (Bickerdike 1907). Optimal tariffs could correlate with CO_2 intensity, since optimal tariffs are higher on more differentiated industries, and clean industries may be more differentiated.

The second set of theories involves political economy. The more influential of these theories focus on organized interest groups (Olson 1965; Grossman and Helpman 1994, 1995; Maggi and Rodríguez-Clare 1998, 2007). Organized industries can provide campaign contributions to politicians, hire lobbyists, organize media campaigns, and in other ways use centralized organization to obtain trade protection.

Variables and Data Sources

Empirical analogues to these political economy explanations come from a range of studies and data sources. Some political economy variables are available separately for each country$\times$industry in Exiobase; I extract these variables and use them for the global analysis. A larger set of political economy variables are available from U.S. data. I use these data to analyze the U.S. only; Appendix Table 1 summarizes the U.S. variables and data sources (Pincus 1975; Caves 1976; Anderson 1980; Ray 1981; Marvel and Ray 1987; Trefler 1993; Rodrik 1995; Baldwin and Robert-Nicoud 2007; Freund and Çaglar Özden 2008).

Appendix A.3 describes these variables in detail. I discuss the one here which turns out to be the most important. I measure each industry's "upstreamness" as the mean position of an industry's output in a vertical production chain (Antràs et al. 2012; Antràs and Chor 2013) or equivalently, as the share of an industry's output sold to relatively upstream industries (Fally 2012).

3 Econometrics

3.1 Trade Policy and CO_2 Intensity

To measure differences in trade policy between clean and dirty industries, I estimate the following:

$$t_{js} = \alpha E_{js} + \mu_j + \epsilon_{js} \tag{1}$$

The dependent variable t is the mean import tariff rate or ad valorem NTBs that destination country j imposes on goods in industry s. In the global data, s represents the foreign industry which produced the good, not the domestic industry which consumed it. For example, the emissions rate E for Mexican imports of steel reflects the mean emissions from steel production in all countries from which Mexico imports, while the tariffs t reflects Mexico's import tariffs on steel. Equation (1) has a j rather than both i and j subscript because the analyses averages across origin countries (weighted by the value of each trade flow) for three reasons: this enhances comparability between tariffs and NTBs, since the latter are defined only by destination country and industry; this helps address the presence of zero trade flows between some origin×destination×industry tuples; and this increases comparability of these regressions with political economy variables, which are observed at the country×industry level. Appendix Table 2 shows qualitatively similar results with separate observations for each exporter×importer×industry ($i \times j \times s$) tuple.

The main explanatory variable, E, represents the tons of CO_2 emitted per dollar of imported good. As discussed earlier, E is calculated from inverting an input-output table, so includes both direct CO_2 emissions (emitted from industry s) and indirect emissions (emitted from industries used as inputs to industry s, and inputs to inputs, etc.).[15]

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. Appendix Table 2 shows qualitatively similar results without these fixed effects. The idiosyncratic error ϵ contains all unmodeled determinants of import tariff rates.

Equation (1) allows a useful interpretation. The parameter α represents the carbon tariff implicit in existing trade policy, measured in dollars of tax per ton of CO_2. For example, $\alpha = 40$ would imply that an additional \$40 of import duties (or NTB ad valorem equivalent) is collected for each additional ton of CO_2 embodied in a good. My finding of $\alpha \approx -90$ implies that current trade policy embodies a carbon subsidy in trade policy of 90 dollars per ton of CO_2.

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.

Measuring CO_2 intensity from an input-output table may involve two types of measurement error. First, the input-output table itself has errors-in-variables. Constructing an input-output table requires judgments of analysts from national statistical agencies and adjustment through linear programming (Horowitz and Planting 2006). Second, prices paid for each fossil fuel vary by industry, and input-output tables lack data on such industry-specific input prices. Both types of measurement error could create attenuation bias in OLS estimates of α.

To address potential measurement error in measures of CO_2 intensity, I use direct emissions as an

[15] Formally, $E_{js} = (\sum_{i \neq j,t} E_{ijst} X_{ijst}) / \sum_{i \neq j,t} X_{ijst}$, where E_{ijst} is the emissions rate from inverting the global input-output table, and X_{ijst} is the value of the trade flow from origin country i and origin industry s to destination country j and destination industry t. The summation excludes $i = j$ because the emissions rate relevant for carbon tariffs and international trade applies only to international imports, not to intra-national trade.

instrumental variable for total emissions. The first-stage regression is

$$E_{js} = \beta E_{js}^{direct} + \mu_j + \eta_{js} \tag{2}$$

The second stage is equation (1). Here E_{js} measures total (direct+indirect) emissions from the input-output table, and E_{js}^{direct} measures direct emissions. The instrument is only designed to address attenuation bias due to measurement error. If measurement error in direct and total emissions is independent, then this instrument will eliminate attenuation bias due to measurement error. Omitted variables and reverse causality are not problems to address 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 on trade policy.[16]

For the U.S. data, this instrument may help correct measurement error since MECS and the CM measure fossil fuel use per physical unit separately for each industry, and MECS does not involve analyst imputation.[17] For the global data, this instrument may matter less since the instrument and endogenous variable are constructed from the same data source, the global multi-region input-output table, and so measurement error in the instrument and endogenous variable may be correlated in the global data.

3.2 Political Economy Explanations

I then test the hypothesis that the association between trade policy and CO_2 intensity reflects variables that are omitted from equation (1) but that both determine trade policy and correlate with CO_2 intensity. I estimate linear regressions including potential variables F_{js} that are believed to explain trade policy, along with CO_2 intensity:

$$t_{js} = \beta E_{js} + \pi F_{js} + \mu_j + \epsilon_{js} \tag{3}$$

I estimate a separate regression for each political economy variable F_{js} and assess which of these political economy variables most attenuates the estimated covariance β between trade policy and carbon intensity.

In separate estimates, I control for all potential political economy explanations at once. I implement this regression using both linear regression and using the least absolute shrinkage and selection operator (Lasso), which is a common machine learning algorithm for automatic model selection (Tibshirani 1996). Identifying which variables Lasso includes in a model can be informative though also sensitive to specification (Mullainathan and Speiss 2017). These regressions test whether each variable, including CO_2 intensity, has additional explanatory power for trade policy beyond these other variables.

It may be informative to distinguish this approach from two others that appear superficially similar

[16] 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, Appendix Table 2 reports results at the $i \times j \times s$ level, which do not require averaging over trading partners, and which finds qualitatively similar patterns of implicit subsidies.

[17] Documentation of U.S. input-output tables does not explicitly mention MECS (Horowitz and Planting 2006). If analysts use MECS to construct the U.S. input-output table, measurement error in the two sources may be correlated. Then using E_{js}^{direct} as an instrument would decrease but not completely eliminate attenuation bias.

but are substantively different. One is the "bad control" problem (Angrist and Pischke 2009) in which a researcher includes intermediate outcomes as controls in a regression of a final outcome on the main variable of interest. Equation (3) is not a case of bad control because the political economy variables F_{js} are not intermediate outcomes that are causally affected by CO_2 intensity and themselves affect trade policy. Instead, F_{js} are the variables that directly affect tariffs. I seek to determine which most accounts for the unconditional covariance between trade policy and CO_2 intensity.

Another substantively different approach is "mediation," which adds intermediate outcomes in a regression of a final outcome of interest on an initial policy change. It then assesses the extent to which adding these intermediate outcomes attenuates the coefficient on the initial policy change. This analysis is not mediation—this is not a causal regression seeking to estimate the ceteris paribus effect of CO_2 intensity on trade policy. Instead, the correlation between CO_2 intensity and trade policy reflects omitted variables. The analysis empirically tests which variables, when omitted, lead to this correlation.

4 Results: Trade Policy and CO_2 Intensity

4.1 Summary Statistics

Table 1 describes the cleanest and dirtiest industries in the global data, ranked by total (direct+indirect) CO_2 emissions. Panel A shows the cleanest five industries while Panel B shows the dirtiest. Column (1) shows mean CO_2 rates across all countries, column (2) shows mean tariffs, and column (3) shows NTBs.

The cleanest five manufacturing industries primarily produce food products and have a mean global emissions rate of 0.37 tons CO_2 per thousand dollars of output. The dirtiest five manufacturing industries mostly produce heavy goods like bricks or steel and have a mean global emissions rate of 1.88 tons CO_2 per thousand dollars of output. Motor vehicles appear relatively clean in these data (also in U.S. input-output tables) because, as discussed earlier, most of the emissions due to vehicles come from a separate good that is complementary, refined petroleum.

It may be informative to calculate the CO_2 externality these numbers imply. If each ton of CO_2 emitted creates a social cost of carbon of \$40 (IWG 2016), this comparison involves multiplying by 40/1000. This calculation implies that globally, pork products create a social cost from CO_2 emissions of about 1.4 percent of product value (=0.34*40/1000). Producing iron and steel creates a CO_2 externality equal to 7 percent of its product value (=1.74*40/1000).

Although Table 1 just lists ten outlier industries, its patterns preview the more general finding that cleaner industries face more restrictive trade policy than dirty industries do. Column (2) shows that the cleanest industries face four times the mean tariff of the dirtiest industries, at 12 versus 3 percent. Column (3) shows a similar difference between the cleanest and dirtiest industries for NTBs (25 versus 5 percent).[18] I now turn to regressions analyzing all industries.

[18] In the anecdotal comparison of Table 1, partly this pattern occurs because manufactured food products are relatively clean but face high levels of protection. Appendix Table 2 separately estimates the main results while excluding manufactured food and agricultural products; it finds that the paper's main findings persist with this sample exclusion though have smaller magnitude.

4.2 Implicit Carbon Tariffs

Tariffs

Figure 1, Panels A and B, plots hypothetical $40/ton carbon tariffs. These are not actual data, but instead depict a proposed policy. Each point in these graphs is a separate country×industry (Panel A, all countries) or industry (Panel B, U.S. only). The tariff rate is a constant multiple of the emissions rate, which makes both graphs linear. In this hypothetical policy, the mean carbon tariff for all countries in Panel B is three percent, which is nearly half of current global mean tariff rates. The mean U.S. carbon tariff is also about three percent, which is slightly larger than prevailing mean U.S. tariffs (Table 2).

Figure 1, Panels C and D, shows actual tariff data. In these graphs, the pattern across industries is the opposite of hypothetical carbon tariffs. The hypothetical carbon tariffs in Panels A and B impose higher tariffs on dirtier industries (positively sloped line), but actual tariffs in Panels C and D impose lower tariffs on dirtier industries (negatively sloped line). Appendix Figure 2 shows qualitatively similar conclusions from graphs weighted by the value of trade flows and from nonparametric regressions.

Table 2 reports regressions corresponding to these graphs. Panels A and B show estimates for the world and U.S., respectively. Column (1) shows a first-stage regression of total CO_2 intensity on direct CO_2 intensity, corresponding to equation (2). Column (2) shows reduced-form regressions of tariffs on direct CO_2 intensity. Column (3) shows OLS regressions of tariffs on total CO_2 intensity. Column (4) reports instrumental variables regressions of tariffs on total CO_2 intensity, instrumented by direct CO_2 intensity. Column (5) weights this instrumental variables regression by the dollar value of each trade flow, which estimates effects for the mean dollar of trade rather than for the mean importer×industry pair. For the U.S., column (5) also provides an efficient response to heteroskedasticity, since U.S. effective tariff rates equal total duties divided by total trade value.

In Table 2, Panel A, the negative signs in columns (2) through (5) imply that global tariffs have an implicit subsidy to CO_2 emissions in trade policy, not a tax. These subsidies are statistically distinguishable from zero at 99.9 percent confidence. Columns (4) and (5) show that the mean subsidy to CO_2 emissions in global tariffs is $30 per ton of CO_2 in unweighted regressions, or $18/ton weighted. In the U.S. estimates (Panel B), column (1) shows that direct CO_2 emissions provide a strong instrument for total CO_2 emissions, with a first-stage F-statistic (equal to the square of the t-statistic) of about 45. The instrumental variables estimates in columns (4) and (5) show that for each additional ton of CO_2 emitted, a good faces 6 to 7 dollars less in import duties.

Figure 2 shows the estimated association between CO_2 intensity and tariffs for the U.S., separately for each year of available data 1989-2017.[19] The red circle shows the point estimate for each year and the vertical bar shows the 95 percent confidence interval. The value for the year 2007 corresponds to Table 2, Panel B, column (4). This graph shows statistically significant negative associations between U.S. tariffs and CO_2 intensity in every year. The estimated U.S. implicit subsidy was $13/ton in 1989,

[19] This graph uses CO_2 intensity from the year 2007 but U.S. import tariffs for each year, so as to isolate changes in trade policy. NTB data are only available for one year.

then decreased gradually to \$6/ton around 1998, and remained near that value through 2017. As Section 5 discusses, the WTO's effort to decrease tariff escalation in the Uruguay Round in the 1990s is one possible explanation for this trend.

Non-Tariff Barriers

Figure 1, Panels E and F, plots NTBs against CO_2 emission rates. These graphs have similar structure to the graphs for tariffs. They show that dirtier industries face less restrictive NTBs and that this relationship has large magnitude in both the global and U.S. data. Some of the cleanest industries have NTB ad valorem equivalent values close to 100 percent, while many of the dirtiest industries face little or no NTB protection.

Table 3 reports regressions corresponding to these graphs. The table structure is similar to the tariff regressions in Table 2. Again these numbers in columns (2) through (5) are all negative, showing a carbon subsidy in trade policy rather than carbon tax, and statistically distinguishable from zero at 99.9% confidence. Columns (4) and (5) show that the implicit subsidy to CO_2 in global NTBs is \$64 in the unweighted regressions or \$72 in the weighted regressions. The instrumental variables estimates in columns (4) and (5) show a large subsidy to CO_2 emissions implicit in U.S. NTBs, of about \$37 to \$44/ton. Summing up subsidies in tariffs and NTBs from Tables 2 and 3 gives the global subsidy that I emphasize of around \$90/ton.

These implicit subsidies appear in both tariffs and NTBs but have larger magnitude (in absolute value) in NTBs, perhaps in part since NTB mean values are greater. The mean U.S. ad valorem equivalent of NTBs is 7 to 9.5 percent, which is about four times the mean tariff rate (Tables 2 and 3). This supports the common claim that U.S. NTBs are more restrictive than U.S. tariffs. Globally, NTBs create a larger barrier to trade than tariffs do, at 9 to 13 percent (NTBs) versus 4 to 6 percent (tariffs).

Implicit Subsidies, by Country

To investigate how these patterns vary by country, I sum together tariffs and the ad valorem equivalent of NTBs as a more complete measure of protection. I then estimate equation (1) separately for each country (hence, these regressions exclude country fixed effects).

Figure 3 plots the result. Each point in this graph describes an estimate of the implicit carbon subsidy for one country. The point for each country is estimated separately. Points on the graph are ordered by the estimated implicit subsidy, with names shown for several countries of interest.

Every country in Figure 3 has a negative value, implying that every country has a carbon subsidy rather than a carbon tariff implicit in trade policy. European countries like France, Germany, Norway, and the UK have among the largest such subsidies, with subsidy values exceeding \$200/ton. Russia, India, and China have smaller subsidies, of under \$200/ton. Figure 4 plots these data in a global map which classifies countries by their implicit subsidies.

The cross-country comparisons in Figures 3 and 4 do not follow easily predictable sensible patterns. Large subsidies appear in both rich regions like the EU and poor regions like Africa; small subsidies also appear in both rich countries like Canada and poorer countries like South Africa. Oil-intensive countries like Saudi Arabia and Iran have among the smallest subsidies, while countries with strict environmental policies like Norway have among the largest. This lack of systematic patterns is consistent with the interpretation, developed in Section 5, that these subsidies are not driven by environmental concern, but instead are due to political economy forces which are correlated with CO_2 intensity.[20]

Sensitivity Analyses and Extensions

Appendix Table 2 reports 15 other methods and samples for estimating these 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 zero 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 5-10 report other ways of cleaning and aggregating data. Row 5 replaces the bottom and top percent of the dependent and independent variables as equal to the 1st and 99th percentile values. Row 6 aggregates the data to 10 regions and 21 industries, described in Appendix Tables 8 and 9, since the quantitative model analyzes this aggregation. Row 7 includes non-manufactured goods. Row 8 uses a dataset defined at the level of a bilateral trading pair and industry (i×j×s rather than j×s). Row 9 uses the same approach but aggregates to the 10 regions and 21 industries of Appendix Tables 8 and 9. Row 10 aggregates to one industry per observation.

Rows 11-15 show other sensitivity analyses. Row 11 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 12 estimates the regression without importer fixed effects. Row 13 uses data from the World Input Output Dataset (WIOD). Row 14 uses data on all greenhouse gases and sources, including nitrous oxide (N_2O), methane (CH_4), emissions from industrial processes, and emissions from land use. Row 15 excludes manufactured agricultural goods and manufactured food products.

Most results in Appendix Table 2 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. Aggregating to a small number of industries (Rows 6 and 9) makes the U.S.-only (but not global) estimates smaller, in part because it leaves the regression with only 21 observations. The WIOD data imply larger implicit subsidies than the Exiobase data do for NTBs, though smaller for tariffs. Finally, excluding agricultural and food manufactured products produces smaller estimates of the implicit subsidies.

[20] In unreported results, I took the estimated country-level subsidy to CO_2 in trade policy plotted in Figures 3 and 4, and regressed it on several country characteristics. This regression finds that a country's GDP per capita, its mean tariff rate, and its quality of environmental management (as measured in Wendling et al. (2018)) are all significantly associated with larger subsidies in absolute value. The regression also controlled for mean NTB rates, mean CO_2 emissions rates, an index of perceived country corruption (Transparency International 2007), and the country's mean upstreamness; these other variables had marginally significant (upstreamness) or no (other controls) association with the level of a country's implicit subsidy. I do not show this cross-country, cross-sectional regression, which has 7 explanatory variables and less than 50 observations, since it may be hard to interpret economically; I mention it because it provides another way to summarize the data in Figures 3 and 4.

I also separately analyze subsidies to CO_2 implicit in cooperative versus non-cooperative tariffs. Some countries that are not members of the World Trade Organization face higher tariffs that are 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.[21]

Appendix Table 3 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 \$6 to \$8/ton in cooperative tariffs and a subsidy of \$60 to \$75/ton in non-cooperative tariffs. Consistent with Figure 3, China does not have an 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 only slightly larger for non-cooperative than for cooperative tariffs.

5 Explanations for the Relationship Between Trade Policy and Pollution

Why do countries impose higher tariffs and NTBs on clean than on dirty goods? Answering this question is not needed to show that this pattern of trade policy exists or to analyze the consequences of changing it, but I investigate this question for a few reasons. The existence of these subsidies is surprising, so the question of why they exist is interesting. Additionally, because no prior research has tested for or demonstrated the existence of these subsidies, explaining why they exist enhances their plausibility. Finally, understanding why these patterns of trade policy occur may provide insight into the political feasibility of changing them.

To investigate reasons for the relationship between trade policy and pollution, I use four approaches: (1) linear and machine learning regressions; (2) nonparametric estimates of the relationship between upstreamness, trade policy, and CO_2 intensity; (3) a qualitative discussion of several trade policy and public finance theories, and (4) a quantitative analysis of one trade policy theory, the "Protection for Sale" model (Grossman and Helpman 1994; Goldberg and Maggi 1999; Gawande et al. 2012).

5.1 Political Economy Explanations: Omitted Variables

Table 4 asks which political economy explanation is the most important omitted variable in regressions of trade policy on CO_2 intensity. It shows regressions of trade protection (tariffs+NTBs) on total CO_2 intensity while controlling for one political economy determinant of trade policy at a time, with specification corresponding to equation (3). Total CO_2 intensity is instrumented with direct CO_2 intensity.

[21]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).

Panels A and B show estimates for all global trade; Panel C shows U.S. estimates. Column (1) includes no controls. Columns (2) through 6 each control for one political economy variable, observed at the level of a country×industry. Column (2) controls for upstreamness, column (3) for intra-industry trade, column (4) for the import penetration ratio, column (5) for the labor share, and column (6) for the mean wage.

Table 4, Panel B, uses other country×industry's data to construct instrumental variables for the focal country×industry. For example, the instrumental variable for the labor share of the Petroleum Refining industry in China equals the mean labor share of the Petroleum Refining industry in all countries besides China. These instrumental variables help address the possibility that some political economy explanations are endogenous. One example would be if trade policy affects wages in a given industry and country but not in the same industry in other countries. If these issues for a particular industry occur within but not across countries, instrumenting with values in other countries helps address these concerns. This is a related approach to analyses of agglomeration and analyses of import competition, which use values in other countries as instruments (Ellison et al. 2010; Autor et al. 2013; Antràs et al. 2017).

Table 4, Panel A, column (1) restates the earlier result that the total subsidy to global CO_2 emissions implicit in global trade policy is around \$90/ton. Column (2) shows that controlling for upstreamness attenuates this estimate by 70%, to \$28/ton. Columns (3) through (6) find that controlling for other political economy variables one at a time only slightly changes the estimated implicit subsidy.

Table 4, Panel B, obtains similar estimates from instrumenting each political economy variable with its mean in other countries. In column (2), controlling for upstreamness completely eliminates the estimated implicit subsidy—the estimated association between CO_2 emissions and trade policy is -\$93 and statistically significant at 99.9% confidence with no political economy controls, but (positive) \$5 and statistically indistinguishable from zero when controlling for upstreamness. Columns (3) through (6) show that instrumenting does not meaningfully change the other estimates. The instruments are all strong, with first-stage F-statistics above 70.

Panel C finds similar patterns using U.S. data. The estimated U.S. subsidy from tariffs and NTBs is \$46/ton (standard error 10). Controlling for upstreamness attenuates this estimate by 90%, to \$5/ton (standard error 10). Other political economy controls do not substantially change the estimated subsidy.

Figure 5 graphs the U.S. estimates from Table 4, along with estimates controlling for other political economy variables that are available for the U.S. but not all countries. Each blue circle in these graphs is the coefficient from a regression of tariffs+NTBs on total CO_2 intensity (instrumented by direct CO_2 intensity), controlling for one political economy variable, and corresponding to equation (3). Each red horizontal line shows a 95% confidence interval. The "Main Estimates" restates results from Table 4, Panel C, column (1). Each of the other numbers controls for one additional variable. The "Firm size: mean" entry, for example, comes from a regression that controls for the mean firm size in each industry.

Figure 5 shows that controlling for most political economy variables one-by-one produces little or no change in the association of trade policy with CO_2 intensity. Only one political economy explanation, upstreamness, substantially attenuates the estimated implicit subsidy, and renders it statistically indistinguishable from zero.

Appendix Table 4 shows sensitivity analyses. Panels A, B, and C show that weighted regressions are qualitatively similar to the unweighted versions. In the weighted and instrumented regressions of Panel B, controlling for upstreamness attenuates the global estimated subsidy from -90.11 (11.95) to 0.46 (20.00). 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 – the Census of Manufactures and the Manufacturing Energy Consumption Survey – 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, and if anything, suggest an even more important role for upstreamness. 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 5 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 far 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 the controls, all except CO_2 intensity have been re-scaled 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. The raw association of trade policy with CO_2 intensity is $-90 (Tables 2 and 3), but with controls this estimate is $-18 to $-28 (Appendix Table 5). Adding these controls with U.S. data also makes the estimated association between trade policy and CO_2 intensity less precise.

All the estimates in Appendix Table 5 identify upstreamness as a strong predictor of trade policy, even conditional on the other political economy variables. Upstreamness is the only explanation which is statistically significant in all specifications. Upstreamness also has large magnitude effects on trade policy. Lasso retains only two variables in the selected model: CO_2 intensity and upstreamness.

Appendix Table 5 does not include "local" or "criteria" pollutants like carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM_{10} or $PM_{2.5}$), sulfur dioxide (SO_2), or volatile organic compounds (VOCs). I follow the existing trade literature and particularly Rodrik (1995) closely in choosing potential political economy variables; once other variables are eligible to be included, the list of variables that one could brainstorm which could in principle influence trade policy is lengthy. "Local" pollutants are also highly correlated with CO_2 emissions, leading to multicollinearity. Regardless, versions of Appendix Table 5 which do include measures of these six local pollutants for U.S. imports (not shown) from the

EPA's National Emissions Inventory find fairly similar results.[22]

5.2 Political Economy Explanations: Why Upstreamness?

Why is an industry's upstreamness strongly correlated with its CO_2 intensity? Using U.S. data from the BEA, Appendix Figure 4 graphs the share of each industry's revenue that is accounted for on the production side by intermediate goods, labor expenditures, profits+taxes, and fossil fuels. Appendix Figure 4 shows that upstream industries use a larger share of fossil fuels than downstream industries do. For the upstream industries, nearly five percent of production costs are devoted to fossil fuels; for the most downstream industries, less than one percent of costs are. Relative to upstream industries, downstream industries spend relatively more on labor and intermediate goods. These patterns have not been previously shown but makes intuitive sense—upstream industries are taking raw materials extracted from the ground and transforming them, while downstream industries depend more on labor and other inputs.

Appendix Figure 4 also helps answer an important question. If downstream goods are just combinations of upstream goods, why would different import tariff rates on upstream versus downstream goods affect CO_2 emissions? Imagine an economy in which upstream goods were made exclusively from coal and downstream goods were made from upstream goods. In this hypothetical economy, upstream and downstream goods would have the same CO_2 intensity, and tariff escalation could not affect global CO_2 emissions. Appendix Figure 4 shows that this hypothetical economy is misleading because downstream industries use as inputs both upstream goods and relatively clean factors like labor. Hence, imposing high tariffs on downstream but not upstream goods can encourage consumers to substitute from demanding relatively clean factors like labor to demanding relatively dirty factors like energy.

Buyers can respond to changes in trade policy in many ways, including substituting between goods, changing total demand for an industry's products, and changing trading partners. To what extent can firms and consumers substitute between industries with different levels of upstreamness? Certainly in examples, goods that are substitutes have different levels of upstreamness and CO_2 intensity. For example, steel and aluminum are likely substitutes, and in the U.S. data which have greater industry detail, steel is both more upstream and more CO_2 intensive than aluminum. To give another example, containers can be made of metal or wood; the metal container industry is both more upstream and more CO_2 intensive in U.S. data than the wood container industry.[23] If one good is more upstream than another, it is not

[22] One could nonetheless hypothesize that countries impose low tariffs and NTBs on dirty industries in an effort to offshore "local" pollution. I am unaware of any evidence of trade policy negotiators seeking this objective. There is ample concern about negotiators worrying in the opposite direction that trade liberalization could allow dirty industries to leave (i.e., low tariffs and NTBs on dirty industries are usually described as a disadvantage rather than an advantage). Regardless, if every country imposes low tariffs and NTBs on dirty industries, this would undermine a single country's effort to offshore "local" pollution, since while one country might offshore production that emits "local" pollution to its trading partners, those trading partners would be doing the same right back.

[23] The first example compares iron and steel mills (NAICS industry 331111) against aluminum sheet, plate, and foil manufacturing (NAICS industry 331315). The second example compares other metal container manufacturing (NAICS industry 332439) against wood container and pallet manufacturing (NAICS industry 321920).

necessarily or usually an input into the other; being more upstream just means that on average more additional processing industries are required before final consumption. More broadly, consumers can substitute between goods in a wide array of patterns; one goal of the quantitative model in Section 6 is to analyze some of these patterns numerically.

Figure 6 shows nonparametric local linear regressions that provide another way to understand the role of upstreamness. Each graph in this figure shows two lines. The downward-sloping dashed blue line shows a nonparametric regression of total CO_2 intensity on upstreamness. This line shows that the most upstream industries are dirtier. The upward-sloping solid red line shows a local linear regression of tariffs on upstreamness, which shows that the most upstream industries have the lowest tariffs. The patterns are similar for global and U.S. data, and for tariffs and NTBs. As mentioned earlier, previous research has not documented this systematic nonparametric relationship between trade policy and upstreamness. In these graphs, the relationships between each of these outcomes (CO_2 intensity, tariffs) and upstreamness are somewhat linear.[24]

Appendix Figure 5 finds remarkably similar patterns in most countries across the world. This figure plots nonparametric relationships between CO_2 intensity and upstreamness, and between trade policy (tariffs+NTBs) and upstreamness, separately for each country in Exiobase. These are analogous to Figure 6, but for each country separately. While this figure provides almost 50 separate small graphs, causal inspection shows the striking "X"-shaped pattern that in most countries, CO_2 intensity increases somewhat steadily with upstreamness, while tariffs and NTBs decrease.

5.3 General Theoretical Explanations

I now discuss informally how theories of trade policy might rationalize these 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 tariffs in non-cooperative policy instruments, and the empirical relevance of upstreamness, are consistent with these theories.

[24] Appendix Figure 3 shows histograms of the same data, which use binned means rather than nonparametric smoothing. This graph organizes the industries into five groups based on their upstreamness. The light blue bars plot mean CO_2 intensity for each group, while the darker red bars plot tariffs or NTBs for each group. This bar chart suggests a similar conclusion as the nonparametric regressions of Figure 6—upstreamness and CO_2 intensity both increase fairly steadily with upstreamness, but the slopes have opposite sign.

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.

Finally, it is worth discussing one potential explanation from public finance. Diamond and Mirrlees (1971) show that optimal commodity taxes apply only to final and not intermediate goods. In this interpretation, while upstreamness accounts for implicit subsidies, the link between upstreamness and trade policy could be caused by government's desire for an efficient tax system rather than by lobbying.

Several reasons suggest that production efficiency does not explain the importance of upstreamness here. First, Diamond-Mirrlees merely states that the optimal tax system has no taxes on intermediate goods, and otherwise does not rank the efficiency of different tax systems by the degree to which they tax intermediate goods. Second, 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. Third, many countries with tariff escalation already have a value-added tax, which makes an additional tax on imported final goods redundant. Finally, even an optimal commodity tax system would include Pigouvian taxes on intermediate goods that generate production externalities.[25]

5.4 Model-Based Estimates: Lobbying Competition and CO_2 Emissions

Appendix B describes a quantitative analysis of how Grossman and Helpman (1994)'s protection for sale framework would interpret this relationship between CO_2 intensity and upstreamness. I put this analysis in the appendix since the general model and its empirical applications to trade policy (though not to trade policy's environmental bias) are well-known. I summarize results as follows. Patterns of trade policy are consistent with a model where politicians set low low tariffs and NTBs on upstream industries because downstream firms lobby for low tariffs on their inputs. Trade policy superficially suggests that

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

politicians prefer low tariffs and NTBs on dirty industries. This pattern is superficial because it merely reflects a correlation between upstreamness and CO_2 emissions.

6 Consequences of Implicit CO_2 Subsidies

6.1 Partial Equilibrium Approximation

I use two approaches to investigate the consequences of trade policy's environmental bias. The first is a partial equilibrium calculation of the annual difference in global tariffs and NTBs between clean and dirty goods:

$$\sum_{s} \hat{\alpha} X_{js} E_{js} \tag{4}$$

This can be interpreted as revenue that a carbon tariff would collect if it had the same pattern as trade policy's environmental bias (i.e., -\$90/ton). The parameter $\hat{\alpha}$ is the implicit carbon subsidy from equation (1). Estimating this quantity does not require detailed assumptions, but also does not allow changes in quantities or prices.

Equation (4) implies that global trade policy provided an implicit subsidy of \$580 billion in the year 2007 (measured in 2016 dollars). This can be calculated simply: 6.5 billion tons of CO_2 are embodied in international trade (including in intermediates), times \$90 in subsidy per ton of CO_2 traded, gives $\$580 \approx 6.5 \times 90$. Using the estimated implicit subsidy $\hat{\alpha}$ with multiple trading partners ($i \times j \times s$) from Appendix Table 2, row 8, implies an implicit subsidy of \$210 billion. These large magnitudes suggest this subsidy may have quantitatively important effects.

To put these estimates in perspective, global direct subsidies to fossil fuels were about \$460 billion in 2007 (IMF 2013). These direct subsidies are a focus of substantial political debate. The CO_2 subsidies in trade policy, which have not been previously highlighted, have a similar magnitude. Of course, a dollar of direct subsidy to fossil fuel could have different and perhaps larger effects on CO_2 than a dollar of indirect subsidy through trade policy.

6.2 Model-Based Analysis

Choice of Counterfactuals

I turn to describe three specific counterfactual policies and then a model to analyze them. I choose these three because they are relevant to this paper's research questions, have some political plausibility, and provide a benchmark to think about other specific policies.[26]

The first counterfactual changes each country's bilateral import tariffs to the country's weighted mean

[26] I abstract from possible strategic responses (see Ossa (2014) for an alternative approach). Besides the complexities and uncertainty of describing possible strategic responses, one possible justification is that most of these counterfactuals keep mean tariffs and NTBs per trading partner constant or lower, so may inspire less retaliation than increasing mean tariffs and NTBs.

baseline bilateral tariff, and similarly for NTBs, with weights equal to baseline trade:

$$t'_{ijs} = \frac{\sum_s t_{ijs} X_{ijs}}{\sum_s X_{ijs}} \qquad \forall i \neq j \tag{5}$$

Here t_{ijs} denotes the baseline tariff rate on goods from origin country i to destination country j and sector s, X_{ijs} denotes the baseline value of bilateral trade, and t'_{ijs} denotes the counterfactual tariff. The counterfactual makes a similar change for NTBs. Policies resembling this counterfactual could result from WTO multilateral negotiations focused on eliminating tariff escalation or from environmentalists lobbying for tariff harmonization between clean and dirty industries. In regions like the EU which already have a climate change policy, politicians could argue that this kind of reform decreases leakage. Such policies might even attract support from dirty industries.

In the second counterfactual, only the EU imposes this policy change:

$$\begin{aligned} t'_{ijs} &= \frac{\sum_s t_{ijs} X_{ijs}}{\sum_s X_{ijs}} && \forall i \neq j; j \in EU \\ t'_{ijs} &= t_{ijs} && \forall j \notin EU \end{aligned} \tag{6}$$

Harmonizing EU trade policy between clean and dirty industries may be somewhat politically feasible since the EU has a domestic climate change policy (the EU Emissions Trading System, a large cap-and-trade market for CO_2), is concerned about leakage, and supports strong environmental policies.

In the third counterfactual, all countries set tariffs and NTBs to zero: $t'_{ijs} = 0 \ \forall i, j, s$.

Model Assumptions

Because the model is similar to the "structural gravity" literature in trade, I describe only the model's assumptions here, and describe additional results and counterfactual methodology in Appendix C. The model is solved using "exact hat algebra" (Dekle et al. 2008), with methods closest to those of Costinot and Rodriguez-Clare (2014).

This approach nests three market structures: perfect competition (Eaton and Kortum 2002), monopolistic competition with homogeneous firms (Krugman 1980), and monopolistic competition with heterogeneous firms (Melitz 2003). I present theory and results for all three market structures. Some trade policy research assumes that each industry uses its own specific factor, which generates rents and gives motives for lobbying. Empirically calibrating quantitative trade models with specific factors is complex; market power in principle provides an alternative motive for lobbying (though in practice monopolistic competition assumes markups are fixed). Allowing for firm heterogeneity does reflect wide dispersion in firms' CO_2 intensities (Lyubich et al. 2018). This model uses assumptions like constant elasticity of substitution utility or fixed markups that only roughly approximate reality. I seek to use leading methods to analyze these counterfactuals while recognizing that even these methods require strong assumptions.

Assumption 1 (Preferences): The representative agent in each destination country has constant elasticity of substitution preferences across varieties and Cobb-Douglas preferences across sectors s:

$$U_j = \prod_s \left(\sum_i \int_0^{M_{ijs}} q_{ijs}(\upsilon_{is})^{\frac{\sigma_s - 1}{\sigma_s}} d\upsilon_{is} \right)^{\frac{\sigma_s}{\sigma_s - 1}\beta_{js}} \tag{7}$$

Here M_{ijs} denotes the measure of varieties in sector s sent from origin country i to destination country j, $q_{ijs}(\upsilon_{is})$ is the quantity of variety υ_{is} traded, σ_s is the elasticity of substitution, and β_{js} is the Cobb-Douglas expenditure share.

Assumption 2 (Firms and Production Technology): Under monopolistic competition, an entrepreneur may pay the fixed cost f_{is}^e, paid in terms of an aggregate input a_{is}, to draw a unique productivity level φ; and to sell in country j, the firm must pay market entry cost f_{ijs}, paid in terms of the destination aggregate input a_{js}. Under all market structures, operating firms face iceberg trade costs $\tau_{ijs} \geq 1$, so must ship $\tau_{ijs} \geq 1$ units for one to arrive. Hence, the firm must purchase $a_{ijs}^v = \tau_{ijs} q_{ijs}/\varphi$ units of the domestic aggregate input a_{is} in order to sell q_{ijs} units in destination j. The aggregate input is a Cobb-Douglas combination of the factor L and an aggregate intermediate good, which is a combination of varieties υ_{is} of intermediate goods:

$$a_{ijs} = (L_{ijs})^{1-\eta_{is}} \prod_k \left(\sum_o \int_0^{M_{ojk}} q_{ojks}(\upsilon_{ok})^{\frac{\sigma_k - 1}{\sigma_k}} d\upsilon_{ok} \right)^{\frac{\sigma_k}{\sigma_k - 1}\eta_{jks}}$$

The aggregate intermediate good is CES in imported varieties shipped from origin country i and industry s to destination country j and industry t , q_{ijst}, and is Cobb-Douglas across industries. Here η_{jks} is the intermediate goods share of industry k for production of industry j in country t. Under monopolistic competition, entrepreneurs draw a productivity φ from the Pareto distribution $prob(\varphi < \varphi_{ijs}^*) = 1 - (\varphi_{ijs}^*)^{-\theta_s}$. Buyers pay bilateral import tariffs t_{ijs} that are levied on production costs but not markups (hence, the tariffs act as "cost-shifters"); tariff revenues are lump-sum rebated to domestic consumers. NTBs are multiplicative with iceberg trade costs, so the full variable trade cost is $\phi_{ijt} \equiv \tau_{ijt}(1+t_{ijt})(1+n_{ijt})$.

Assumption 3 (Pollution): CO_2 emissions come from $Z_{is} = \gamma_{is} R_{is}/P_{is}$. Here Z_{is} are the tons of CO_2 emitted to produce goods from industry s in country i, R_{is} is country$\times$sector revenue, and P_{is} is the country$\times$sector price index. The coefficient γ equals the tons of CO_2 per real unit of output in country i and sector s.

Assumption 4 (Market Clearing): Market clearing for labor and trade balance are $L_i = \sum_s L_{is}$ and $\sum_{j,s} X_{ijs} = \sum_{j,s} X_{jis} - D_i$. Here L_{is} is factor supply, D_i are trade deficits, and X_{ijs} is trade.

To analyze this model, I assume a competitive equilibrium, i.e., that consumers maximize utility, firms maximize profits, and markets clear. This gives rise to several equilibrium relationships that Appendix C lists in detail: the unit cost function, a gravity expression for trade flows, country$\times$sector expenditure; country$\times$sector revenues, and national income. I rewrite these equations in changes using exact hat algebra, which produces a system of nonlinear equations. For baseline data, these equations hold exactly.

Under counterfactual tariffs or NTBs, I solve this system to find the changes in prices and firm entry that make it hold with equality. Finally, I use these to find the resulting change in real income and pollution:[27]

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

$$\hat{Z}_i = \frac{\sum_s \gamma_{is} \hat{R}_{is} R_{is} / \hat{P}_{is} P_{is}}{\sum_s \gamma_{is} R_{is} / P_{is}}$$

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

I primarily apply the model using data from Exiobase, though also show results using WIOD. For computation, I aggregate the data to 10 regions and 21 industries, shown in Appendix Tables 8 and 9. I assume intra-regional tariffs are zero. Three regions comprise the EU: Western, Southern, and Northern Europe.

I use sector-specific trade elasticities from aggregating studies that estimate these parameters: Caliendo and Parro (2015), Shapiro (2016), Bagwell et al. (2018), and Giri et al. (2018). Within a study, I aggregate multiple estimates for a sector using inverse variance weighting, which minimizes variance (Hartung et al. 2008).[28] Appendix C discusses estimation of other parameters and equilibrium uniqueness.

Counterfactuals: Results for Main Counterfactual of Interest

Table 5, row 1 analyzes the first counterfactual, in which each country sets the same tariffs on clean and dirty industries, as in equation (5). Columns (1a) through (1c) show the percentage change in global CO_2 emissions. Columns (2a) through (2c) show the percentage change in global real income, defined as the weighted sum of country-specific changes in real income, where the weights are each country's baseline real income. Columns (3a) through (3c) show the change in CO_2 if trade policy was scaled so global real income did not change. This is calculated as the change in real income minus the change in CO_2 emissions.[29] Columns (1a), (2a), and (3a) represent estimates from a model of perfect competition (Eaton-Kortum or EK), columns (1b), (2b), and (3b) represent estimates from a model of monopolistic competition with homogeneous firms, and columns (1c), (2c), and (3c) represent results from a model of monopolistic competition with heterogeneous firms.

I find that this counterfactual of harmonizing trade policy between clean and dirty industries would

[27]This measure $\hat{V}_j$ excludes disutility from CO_2 emissions. It is simple to include a term $\left(\sum_i Z_i\right)^{\delta_j}$ on the right of equation (7) capturing the disutility from global CO_2. Then the full change in utility is $\hat{V}_j \hat{Z}^{\delta_j}$, with $\hat{Z} = \sum_i (\hat{Z}_i Z_i) / \sum Z_i$. Because there is little consensus on country-specific climate damages δ_j, I report global changes in real income and CO_2 emissions separately. I do discuss the value of global climate damages, which is analogous to $\hat{Z}^{\delta}$.

[28]I take the median estimate across studies since confidence intervals for Giri et al. (2018) are small enough relative to the other papers that inverse variance weighting across studies implicitly puts disproportionately high weight on that study. Bartelme et al. (2018) take the median estimates across these studies to estimate trade elasticities.

[29]Differences in trade elasticities across industries and trade value across countries mean these counterfactuals can change trade's volume and benefits even if they don't change mean tariffs or NTBs.

decrease global CO_2 emissions but increase global real income. Under perfect competition, global CO_2 emissions would fall by a fourth of a percentage point and global real income would rise by nearly a percentage point (Table 1, row 1). Holding global real income were fixed, this counterfactual would decrease CO_2 emissions by over one percentage point. These patterns are similar under models with monopolistic competition, but the magnitudes are larger. Under homogeneous firms this counterfactual would decrease global CO_2 emissions by 1 percent. Under heterogeneous firms, this policy would decrease global CO_2 emissions by 2 percent. The larger estimates under monopolistic competition echo this kind of pattern in other settings that allow for multiple goods and input-output links (Balistreri and Rutherford 2012; Costinot and Rodriguez-Clare 2014).

Appendix Table 7, Panel A, rows 2-4, separates these effects into scale, composition, and technique, which is a common decomposition in environmental economics (Grossman and Krueger 1995; Levinson 2009). Scale equals the change in global real output; composition equals the change in global output shares across industries, valued at baseline emission rates; and technique equals the change in emissions per unit output within each global industry, evaluated at baseline composition.[30] A majority of the change in emissions comes from technique, which includes reallocating production within an industry to countries that emit less CO_2, decreasing emissions from transporting goods within an industry, and other forces. The composition effect, which comes from decreasing the real output of dirty industries and increasing the real output of cleaner industries, also accounts for some of the decrease in CO_2.

Appendix Table 7, rows 5 through 13, reports sensitivity analyses using other data, parameter values, and methods. Panel A considers counterfactuals which adjust all trade policy, which Panel B considers counterfactuals which only change tariffs and NTBs for trade in manufactured goods. Most of these estimates find qualitatively similar results to the main estimates. Most estimates in columns (3a) through (3c) show that if trade policy is scaled to hold global income fixed, this counterfactual decreases global CO_2 emissions by roughly 1 to 5 percentage points. Columns (3a) through (3c) show that implementing this policy for only manufacturing leads to somewhat smaller estimated effects. Implementing this policy for tariffs only or NTBs only lead to smaller magnitude effects. These patterns make intuitive sense—the more trade this kind of counterfactual changes (all trade versus manufacturing only, tariffs and NTBs versus only one of these instruments, etc.), the more the counterfactual affects CO_2.

Two comparisons suggest these magnitudes are economically important. One is social costs. At a social cost of carbon of \$40 and given emissions in year 2007 of 37 billion tons CO_2 and 49 billion tons of CO_2-equivalent from all greenhouse gases (Climate Watch 2019), this counterfactual would decrease global climate damages by \$15 to \$98 billion per year.

Another comparison is against other climate change policies. The Waxman-Markey bill, which passed the House but not the Senate in 2009, would have created a U.S. cap-and-trade market for CO_2. The European Union Emissions Trading System (ETS), a large cap-and-trade market for CO_2, is the world's

[30]Formally, this decomposition comes from writing 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 $dZ = dX/X + d\kappa/\kappa + de/e$; 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.

largest climate change policy (excluding China's incipient cap-and-trade market). I calculate that these policies would decrease global CO_2 emissions by very roughly 2.6 percent and 1.1 percent, respectively.[31] By comparison, I calculate that this trade policy counterfactual would decrease global greenhouse gas emissions by 1 to 5 percent, which is a similar amount or moderately more than the ETS has. These calculations do compare a global trade policy reform against actual unilateral climate change policies, though most climate change policy to date has involved individual countries.

6.3 Other counterfactual policies

Table 5, row 2, considers a counterfactual like this that only the EU imposes, as in equation (6). Row 3 considers a counterfactual in which all countries eliminate import tariffs and NTBs.

The effects of the EU policy resemble those of the global policy from row 1, but the magnitudes are smaller. This counterfactual EU policy would decrease global CO_2 emissions by up to 2 percentage points while increasing global real income by between 0.5 and 0.8 percentage points. Because the global policy in row 3 eliminates tariffs and NTBs, it increases global real income by 1 to 2 percentage points. These changes in real income increase global CO_2 emissions. Columns (3a) to (3c) show that if global real income is held fixed, the global policy in row 3 would decrease CO_2 emissions by up to 2 percentage points. Why does removing all global tariffs and NTBs increase global real income by these limited amounts? This magnitude is not large both because baseline global tariffs and NTBs are modest and because these families of quantitative trade models generally show modest effects of trade policy reforms (Costinot and Rodriguez-Clare 2014).

More broadly, why do so many of these 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.

7 Conclusions

This paper asks a simple but new question: how and why do tariffs and non-tariff barriers (NTBs) differ between clean and dirty industries? "Dirty" goods are defined by the total CO_2 emitted to produce a dollar of output. I find a simple answer: tariff and NTB rates are substantially higher on clean than on

[31] The Waxman-Markey bill would have decreased U.S. greenhouse gas emissions by 17 percent in the year 2020 relative to 2005 levels. The U.S. accounted for 15 percent of global CO_2 emissions in 2005. Although the Waxman-Markey bill did not pass, U.S. emissions were similar in 2014 as in 2005 (Climate Watch 2019). Assuming the Waxman-Markey bill would have decreased U.S. emissions by 17 percent, it would have decreased global emissions by 2.6 percent (=0.15*0.16). In 2005, the EU emitted 11 percent of global CO_2-equivalent (Climate Watch 2019). Some research estimates that the EU ETS decreased EU emissions relative to a counterfactual by about 10 percent (Dechezlepretre et al. 2018), which implies that the EU ETS decreased global emissions by about 1.1 percent.

dirty goods. This relationship appears in most countries, in cooperative and non-cooperative tariffs, and whether weighted by trade value or unweighted.

At a broad level, this paper suggests that trade policy can have important impacts on environmental outcomes. The implicit subsidy to CO_2 in trade policy this paper analyzes, which has not been previously identified, totals \$210 to \$580 billion per year. For comparison, all direct global subsidies to fossil fuel consumption, which are a major focus of political debates involving the U.S., EU, World Bank, and IMF, together total about \$470 billion per year. General equilibrium model-based analyses require strong assumptions but suggest that if countries imposed similar tariffs and NTBs on clean and dirty industries, global CO_2 emissions would fall by 1 to 5 percentage points, while global real income would largely not change. This change in global CO_2 emissions is comparable to the estimated effects of the European Union Emissions Trading System or the U.S. Waxman-Markey Bill, which are two of the world's largest actual or proposed climate change policies.

I find that trade policy has this subsidy because political economy variables that determine trade policy are correlated with CO_2 emissions. The data show an important role for an industry's upstream location—the extent to which it sells to other firms versus final consumers. One could conjecture various political economy explanations for why upstream industries face lower tariffs and NTBs. I describe theory and evidence consistent with one explanation: firms lobby for high protection on their own outputs but low protection on their intermediate inputs. Because industries can be well organized but final consumers generally are not, countries end up with higher tariffs and NTBs on downstream (and clean) goods, and lower tariffs and NTBs on upstream (and dirty) goods.

These conclusions are relevant to policy. Climate change is a classic externality that would be addressed efficiently with a Pigouvian tax on CO_2 emissions. Today, however, a fifth of global output faces carbon prices, and existing carbon prices are heterogeneous and far below typical estimates of the social cost of carbon emissions. Countries that do implement carbon prices face concerns that they will decrease the competitiveness of domestic energy-intensive industries and cause "leakage" of dirty production from regulated to unregulated regions. A common proposal to address these concerns is a tariff that is proportional to the carbon embodied in imported goods, usually called a carbon tariff or carbon border adjustment. The merits of carbon tariffs have been debated, and no such policy has yet been fully implemented. I show that countries are imposing greater protection on clean than on dirty goods, so instead of internationally adopting a carbon tariff, as researchers and policymakers have proposed, most countries have implicitly created a carbon subsidy in trade policy. Even in the absence of a formal carbon tariff, using bilateral and multilateral trade policy negotiations to decrease this environmental bias of trade policy could help address climate change. This proposal is particularly relevant in regions like the EU which already have a domestic carbon price, but which currently have trade policies that may be encouraging leakage of dirty production to other regions rather than preventing it.

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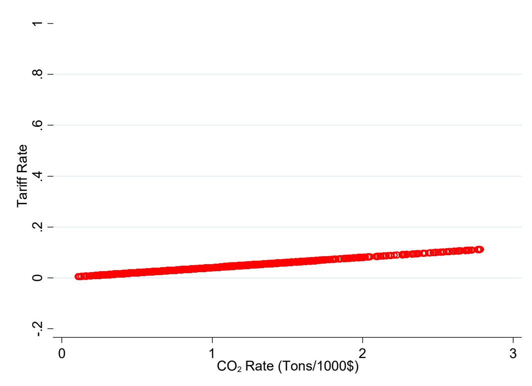
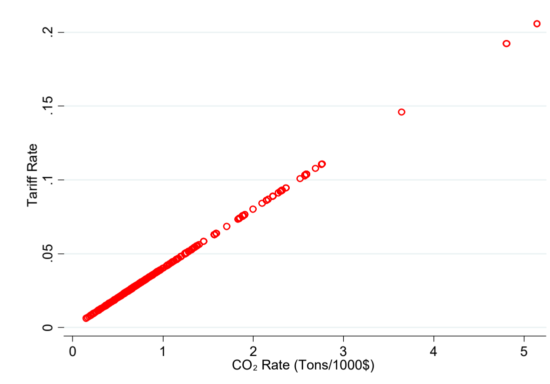
Figure 1—Trade Protection Versus CO_2 Emission Rates

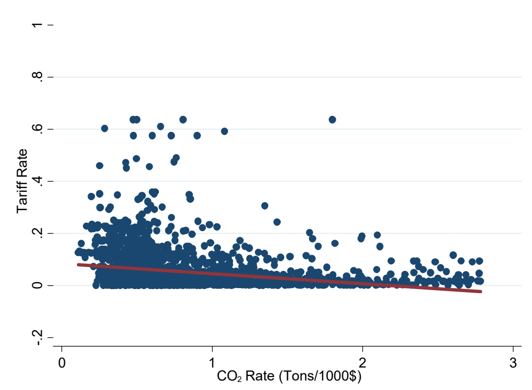
Panel A. Global hypothetical carbon tariff



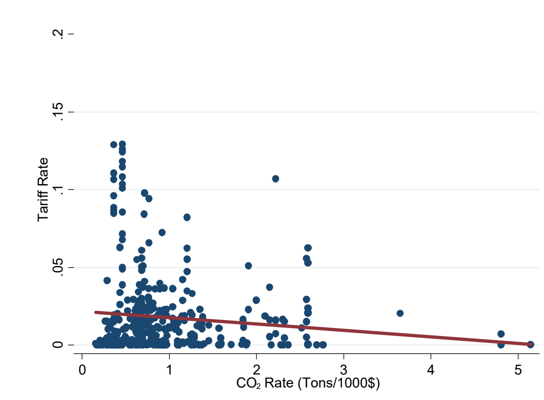
Panel B. U.S. hypothetical carbon tariff



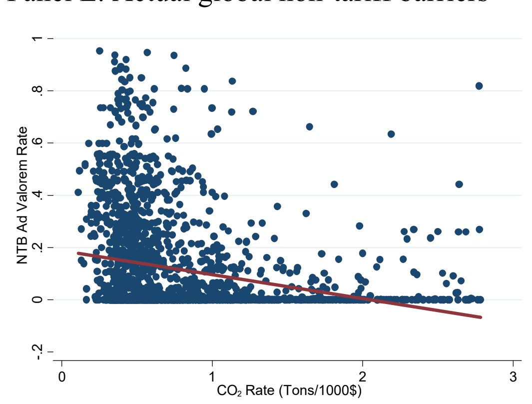
Panel C. Actual global tariffs



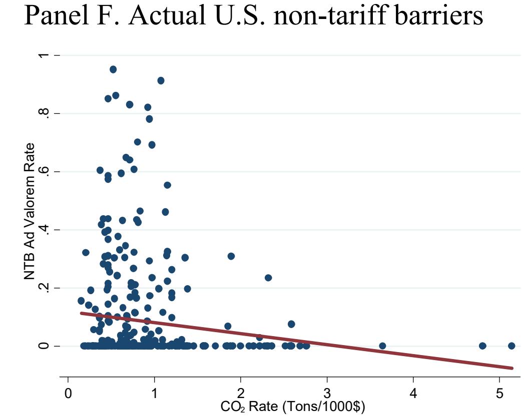
Panel D. Actual U.S. tariffs



Panel E. Actual global non-tariff barriers

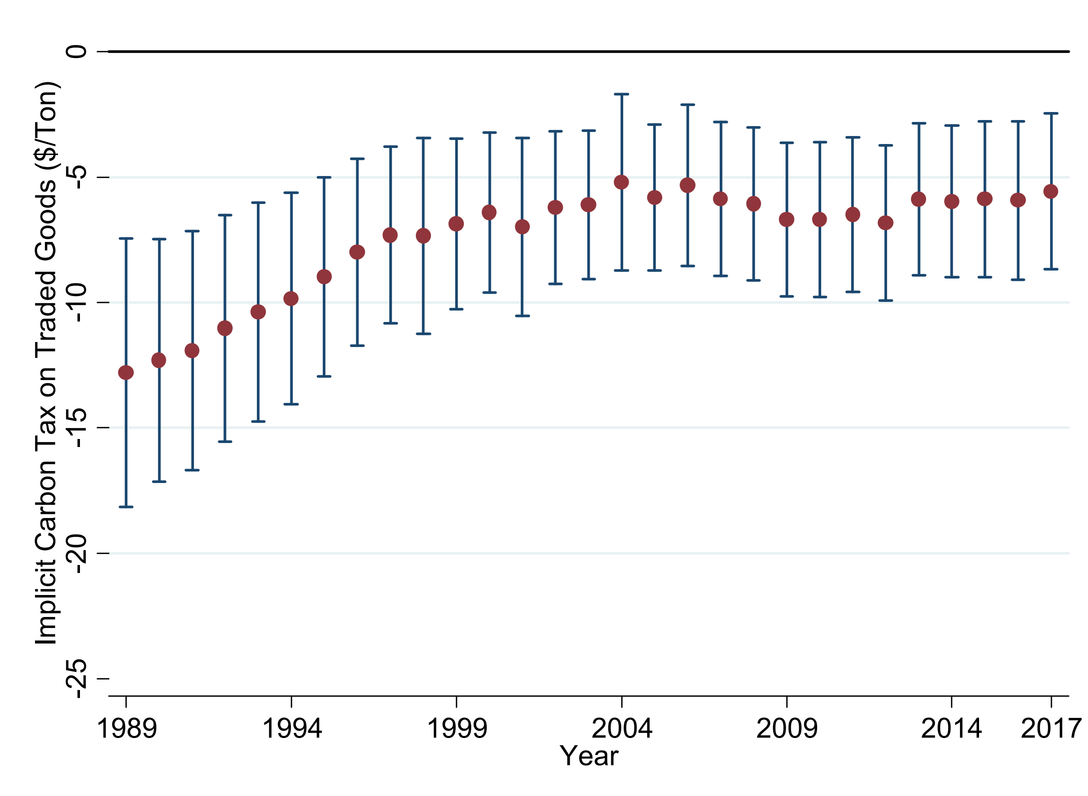


Panel F. Actual U.S. non-tariff barriers



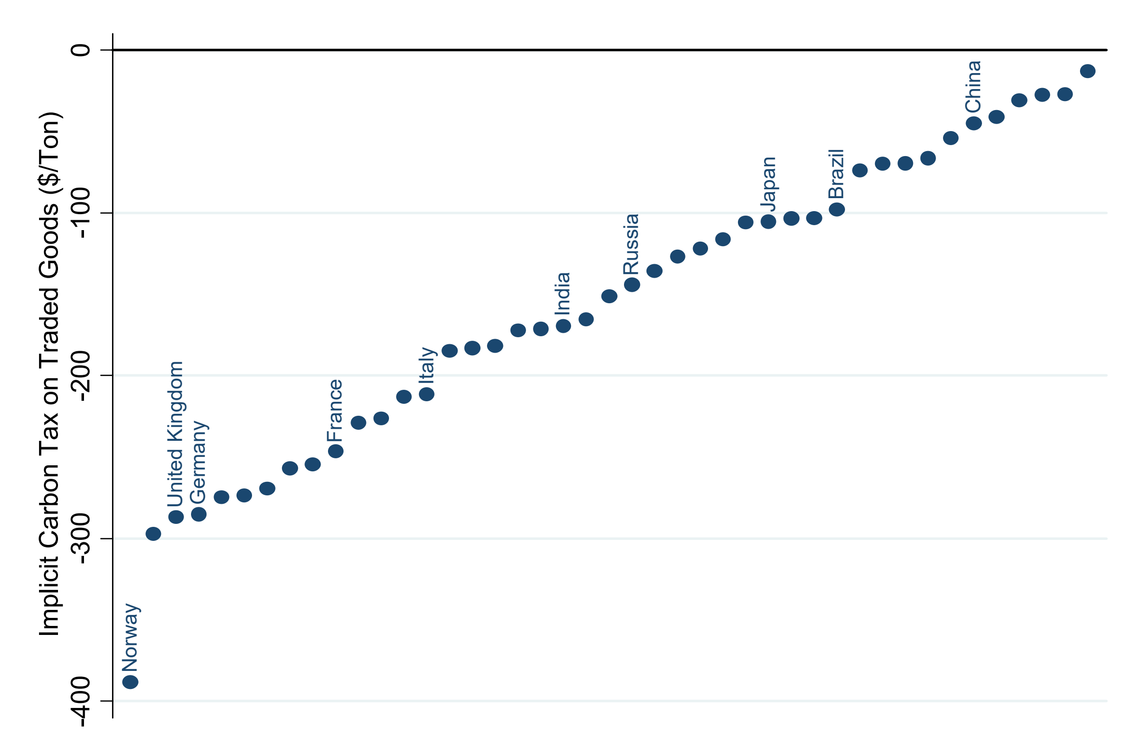
Notes: Panels A and B plot a hypothetical carbon tariff of $40/ton. Each point in global data is an importer*industry pair; each point in U.S. data is an industry. CO_2 rate is total (direct+indirect) emissions measured from inverting an input-output table. Line is linear trend; in Panels C and E, line is fitted from regressions including importer fixed effects. Each graph excludes the top 1% of CO_2 rates, tariffs, and NTB rates.

Figure 2—Correlation Between U.S. Import Tariffs and CO_2 Emission Rates



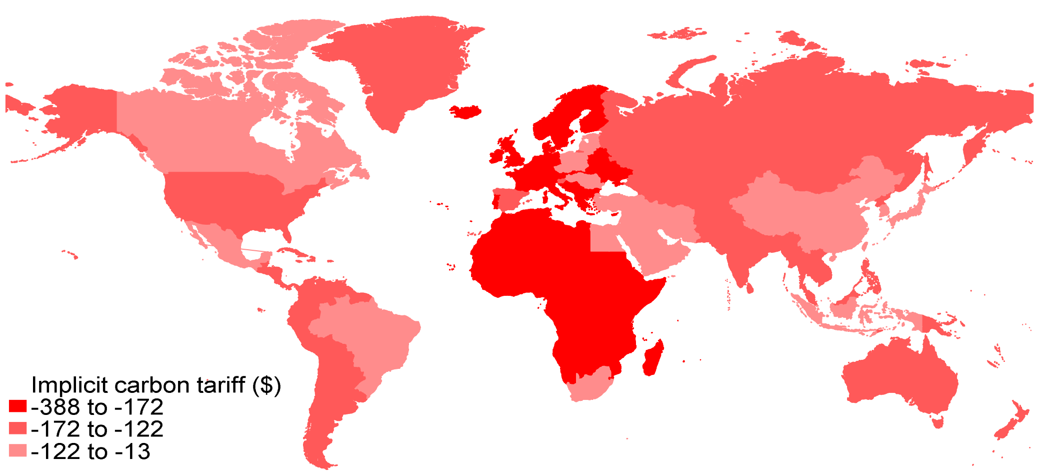
Notes: Implicit carbon tax is the coefficient from a regression of import tariffs on CO_2 emission rates, as in equation (1). Graph shows a separate regression for each year. Emissions intensity is estimated from 2007 input-output tables and applied to all years. Circles show the coefficient estimates, bars show 95% confidence intervals. Regressions use instrumental variables, total CO_2 is instrumented with direct CO_2.

Figure 3—Covariance of Trade Protection and CO_2 Emission Rates, by Country



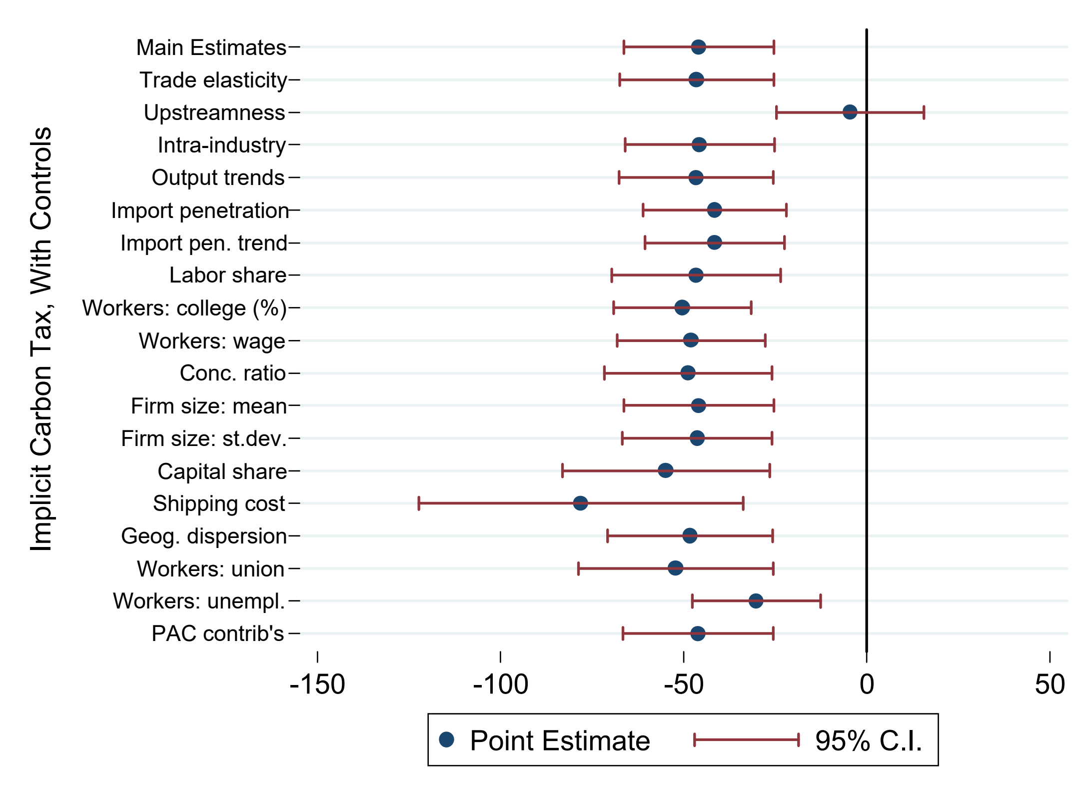
Notes: Implicit carbon tax is the coefficient from a regression of import tariffs plus NTBs (ad valorem equivalent) on CO_2 emission rates and a constant, separately for each country. Data from year 2007. Graph excludes five Exiobase countries missing NTB data: Bulgaria, Cyprus, Malta, Slovakia, and Taiwan.

Figure 4—Implicit Carbon Tax on Traded Goods, by Country



Notes: Implicit carbon tax is the coefficient from a regression of import tariffs plus NTBs (ad valorem equivalent) on CO_2 emission rates and a constant, separately for each country. Data correspond to Figure 3. Graphs include five rest-of-world groups, one per continent.

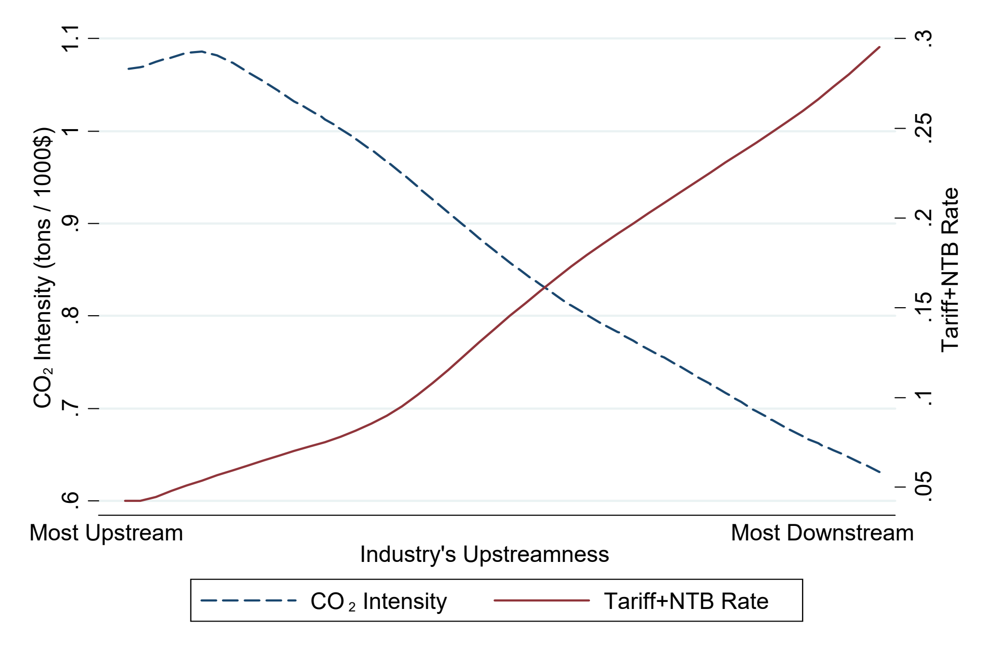
Figure 5—Political Economy Explanations for CO_2 Subsidies Implicit in U.S. Imports



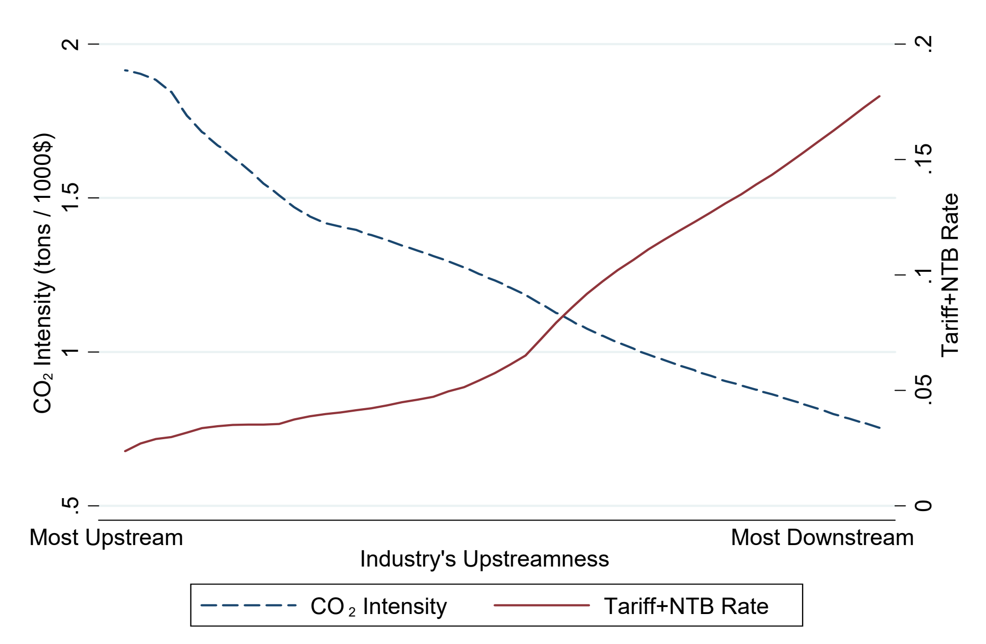
Note: each blue circle represents the coefficient on total CO_2 intensity, instrumented by direct CO_2 intensity, from a regression of tariffs+NTBs on CO_2 intensity. The red bar depicts the 95 percent confidence interval. Each regression includes one additional political economy control, indicated at the left part of the graph.

Figure 6—Upstreamness, CO_2 Intensity, and Trade Policy

Panel A: All Global Trade



Panel B: U.S. Only



Notes: solid line is local linear regression of tariffs or NTBs on upstreamness. Dashed line is local linear regression of CO_2 intensity on upstreamness. Each observation is an importer*industry (Panels A and B) or an industry (Panels C and D). All lines use Epanechnikov kernel with bandwidth of 0.75.

Table 1—Cleanest and Dirtiest Manufacturing Industries in Global Data

	CO_2 Rate (Tons/1000 $) (1)	Import Tariff Rate (2)	Non-Tariff Barriers (3)
Panel A. Cleanest industries			
Pork processing	0.34	0.16	0.37
Meat products n.e.c.	0.36	0.16	0.37
Sugar refining	0.37	0.25	0.42
Wood products	0.37	0.02	0.03
Motor vehicles	0.40	0.04	0.05
Mean of cleanest 5 industries	*0.37*	*0.12*	*0.25*
Panel B. Dirtiest industries			
Bricks, tiles	1.54	0.02	0.02
Coke oven products	1.64	0.01	0.01
Iron and steel	1.74	0.02	0.02
Phosphorus fertilizer	1.93	0.04	0.11
Nitrogen fertilizer	2.53	0.04	0.11
Mean of dirtiest 5 industries	*1.88*	*0.03*	*0.05*

Notes: CO_2 rates are measured in metric tons of CO_2 per thousand dollars of output, calculated by inverting a global multi-region input output region from Exiobase. Dollars are deflated to real 2016 values using U.S. GDP deflator. Global refers to the mean value across all countries, weighted by the value of output; industries ordered based on global emissions; n.e.c. means not elsewhere classified. Import tariffs are ad valorem and measured in year 2007 CEPII Macmap data. Non-tariff barriers are ad valorem, from Kee et al. (2009).

Table 2—Association of Import Tariffs and CO_2 Emissions Rates

	FS	RF	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
Panel A. All global trade (global input-output table)					
CO_2 rate	1.23***	-37.21***	-40.00***	-30.17***	-18.06***
	(0.02)	(4.63)	(4.20)	(3.44)	(3.08)
N	2,021	2,021	2,021	2,021	2021
Dependent Variable Mean	0.001	0.064	0.064	0.064	0.038
Panel B: U.S. Imports (U.S. data)					
CO_2 rate	1.27***	-7.43***	-4.70***	-5.87***	-7.08***
	(0.19)	(1.99)	(1.39)	(1.57)	(2.72)
N	382	382	382	382	382
Dependent Variable Mean	0.001	0.018	0.018	0.018	0.016
Weighted					X

Notes: Table shows regressions of import tariffs on CO_2 rates. Panel A uses global Exiobase data; Panel B uses U.S. data. Each observation in Panel A is an importer×industry; each observation in Panel B is an industry. Panels A includes importer fixed effects. All regressions include a constant. The endogenous variable is the total CO_2 emissions rate (tons/$) measured from inverting the input-output matrix, which accounts for both primary fossil fuels used in an industry and emissions embodied in intermediate goods used in the industry. For Panel A, the instrument is the direct CO_2 emissions rate from the input-output table. For Panel B, the instrument is the CO_2 emissions rate measured from MECS and CM, which accounts for primary fossil fuels used in an industry and electricity consumed in the industry. Emissions rates measured in metric tons of CO_2 per dollar of output. Output is measured in 2016 US$, deflated with the U.S. GDP deflator. FS is first-stage, RF is reduced-form. All data from year 2007. Weights in column (5) are value of imports. Robust standard errors in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Table 3—Association of Non-Tariff Barriers and CO_2 Emissions Rates

	FS	RF	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
Panel A. All global trade (global input-output table)					
CO_2 rate	1.23***	-78.33***	-85.58***	-63.50***	-72.17***
	(0.02)	(10.74)	(8.45)	(8.02)	(11.29)
N	2,021	2,021	2,021	2,021	2,021
Dep. Var. Mean	0.001	0.126	0.126	0.126	0.088
Panel B. U.S. imports (U.S. data)					
CO_2 rate	1.27***	-55.87***	-38.99***	-44.13***	-36.49***
	(0.19)	(15.57)	(6.74)	(10.43)	(12.35)
N	380	380	380	380	380
Dep. Var. Mean	0.001	0.095	0.095	0.095	0.070
Weighted					X

Notes: Table shows regression of NTB rates on CO_2 rates. Panel A uses global Exiobase data; Panel B uses U.S. data. Each observation in Panel A is an importer*industry; each observation in Panel B is an industry. Panels A includes importer fixed effects. All regressions include a constant. The endogenous variable is the total CO_2 emissions rate (tons/$) measured from inverting the input-output matrix, which accounts for both primary fossil fuels used in an industry and emissions embodied in intermediate goods used in the industry. For Panel A, the instrument is the direct CO_2 emissions rate from the input-output table. For Panel B, the instrument is the CO_2 emissions rate measured from MECS and CM, which accounts for primary fossil fuels used in an industry and electricity consumed in the industry. Emissions rates measured in metric tons of CO_2 per dollar of output. Output is measured in 2016 US$, deflated with the U.S. GDP deflator. FS is first-stage, RF is reduced-form. All data from year 2007. The dependent variable is the ad valorem NTB rate from Kee et al. (2009). Weights in column (5) are value of imports. Robust standard errors in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Table 4—Political Economy Explanations for Implicit Carbon Taxes

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All global trade						
CO_2 rate	-93.40***	-28.02***	-93.96***	-96.08***	-93.59***	-93.31***
	(10.17)	(7.67)	(10.29)	(10.19)	(10.20)	(10.21)
N	1,990	1,990	1,990	1,990	1,990	1,990
Panel B. All global trade, instrument for political economy						
CO_2 rate	-93.40***	5.15	-101.15***	-109.74***	-91.83***	-93.24***
	(10.17)	(10.10)	(11.81)	(11.73)	(10.57)	(10.25)
K-P F Statistic	—	1,404.36	262.26	97.73	71.52	135.64
N	1,990	1,990	1,990	1,990	1,990	1,990
Panel C. U.S. imports						
CO_2 rate	-46.16***	-4.82	-46.01***	-42.94***	-46.95***	-47.93***
	(10.48)	(10.22)	(10.46)	(11.60)	(11.80)	(10.25)
N	338	338	338	338	338	338
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 (Panel C). In all regressions, CO_2 rate is the total CO_2 rate (tons/$) from inverting an input-output table, which is instrumented with the direct CO_2 rate. In panel B, each political economy variable (upstreamness, intra-industry share, etc.) is instrumented with the mean of each political economy variable in the industry of interest across all other countries. Panels A and B use Exiobase data, panel C uses U.S. data. Panels A and B include country fixed effects. All regressions include a constant. Robust standard errors in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Table 5—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare, General Equilibrium Model Estimates

	CO_2 Emissions			Real Income			CO_2, Fix Income		
	EK	Krugman	Melitz	EK	Krugman	Melitz	EK	Krugman	Melitz
Counterfactual	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)
1. Tariffs, NTBs to mean	-0.26%	-1.22%	-2.14%	0.89%	1.44%	1.16%	-1.15%	-2.66%	-3.29%
2. Tariffs, NTBs to mean, EU only	-0.20%	-1.19%	-1.00%	0.52%	0.70%	0.57%	-0.72%	-1.89%	-1.57%
3. No trade policy	0.50%	0.19%	1.17%	0.90%	1.23%	1.47%	-0.40%	-1.04%	-0.31%

Note: 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. EK refers to model of perfect competition (Eaton and Kortum 2002); Krugman refers to a model of monopolistic competition with homogeneous firms (Krugman 1980); Melitz refers to a model of monopolistic competition with heterogeneous firms (Melitz 2003).

Online Appendix: The Environmental Bias of Trade Policy

Joseph S. Shapiro
UC Berkeley and NBER
joseph.shapiro@berkeley.edu

A Data Details

A.1 Concordances

For Figure 2, I concord North American Industry Classification System (NAICS) codes across years using concordances from the U.S. Census Bureau (https://www.census.gov/eos/www/naics/concordances/concordances.html, visited Dec 4, 2018). These values are calculated at the industry definition of an input-output table, which I link to NAICS codes for comparability with other data in the paper, using a concordance from the Bureau of Economic Analysis.

A.2 Global Input-Output Data

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

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

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

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

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. For each greenhouse gas separately, I replace emissions from nitrogen fertilizer production with emissions from phosphorus fertilizer emissions from the same country. Additionally, for the crude oil extraction industry, I replace non-combustion methane emissions with combustion methane emissions. In both cases, raw data from Exiobase exceed estimates from other sources. 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.

In the sensitivity analysis using WIOD, I measure environmental outcomes using data on total CO_2 emissions. I replace the roughly 5 percent of 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 recode 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.3 U.S. Political Economy Variables

I group the U.S. political economy variables into those reflecting the demand for protection from industries and their consumers, and those reflecting the supply of lobbying from industries and their consumers. Optimal tariffs are perhaps the simplest. I use estimates of the export supply elasticity for the U.S. (Broda et al. 2008).

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).

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. Industries more exposed to foreign trade have more to gain from protection. I measure the import penetration ratio as total imports divided by the value of shipments, in levels for the year 2007 and as a trend over the period 2002-2007. 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. 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.[1]

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. I calculate mean firm size as the total value of shipments for the industry divided by the total number of establishments in the industry. I also 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. 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. I measure geographic dispersion as entropy across states.[2] 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.[3] Unions provide an organized association to lobby for protection, so I measure unionization rates using processed values from the May 2007 CPS (Hirsch and MacPherson 2003). I also use one direct though incomplete measure of lobbying on contributions to Political Action Committees (PACs).

Upstreamness turns out to be the most relevant of these variables. Appendix Figure 1, Panel D, plots upstreamness separately for all global production and for U.S. production. In all these graphs, the most upstream industries are on the left and the most downstream

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

[2] 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.

[3] I measure unemployment rates of workers where industry is defined according to the current or most recent industry worked.

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 do exclude five countries that are in Exiobase but that I hence exclude from much of the analysis: Bulgaria, Cyprus, Malta, Slovakia, and Taiwan.

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.

B Protection for Sale Quantitative Interpretation

I discuss in detail how one specific trade policy framework, a lobbying competition version of "Protection for Sale," (Grossman and Helpman 1994; Gawande et al. 2012) might interpret this paper's results. This framework provides one formal rationale for interpreting upstreamness as a substantive cause of trade policy.

Here I sketch this framework; Gawande et al. (2012) provide details. Politicians value both social welfare and campaign contributions. Industries may provide campaign contributions in order to obtain trade protection, but protection decreases social welfare. I assume that all industries are organized but no consumers are.[4] The framework implies that an industry's location in vertical production chains affects its demand for tariffs.[5]

From this model, the first-order conditions for the government's choice of tariffs can be written as follows:

$$\frac{t_i}{1+t_i}\frac{m_i}{y_i}|e_i| = \beta_1 + \beta_2 U_i + \eta_i \tag{2}$$

Here t_i represents tariffs or NTBs of industry i; m_i represents the industry's imports and y_i its gross output; e_i is the import demand elasticity, and U_i measures the share of an industry's output sold to other firms versus final demand, which is a basic measure of upstreamness.

[4] This is consistent with some of the literature, though not all. I estimated though do not report models allowing for interactions with indicators for whether industries are above a given percentile of the distribution of PAC campaign contributions (median, 25th percentile, 75th percentile, etc.), which can be used as a proxy for being organized (Goldberg and Maggi 1999), but in these data these interactions were insignificant. Because most industries in these data have some level of campaign contributions, one interpretation is that these industries are all organized to some degree.

[5] This framework allows the most direct interpretation in democracies where politicians run campaigns that benefit from contributions. In non-democratic countries, industries (including state-owned firms) may still influence government decisions through political support, financial support, and other forms of influence besides campaign contributions.

A few comments may help clarify this equation. This model predicts that $\beta_1 = -\beta_2$ represents the number of dollars of campaign contribution that politicians would exchange for a dollar of social welfare. Finding $\beta_1 = 5$ or $\beta_2 = -5$, for example, would imply that politicians would trade off five dollars of campaign contributions for one dollar of social welfare. The model also predicts that this coefficient is equal for downstream and upstream industries (β_1 and β_2, respectively). Additionally, it predicts $\beta_1 > 0$ and $\beta_2 < 0$—the left-hand side variable, which represents a measure of trade protection scaled by import exposure and the demand elasticity for an industry's products, should be lower on upstream industries.

Appendix Table 6 presents estimates related to equation (2). Column 1 estimates this equation directly. Panel A shows tariffs and Panel B shows NTBs. This model assumes non-cooperative trade policy, which best describes NTBs; I show results for tariffs also for reference and consistency with the rest of the paper.

Appendix Table 6, column 1, finds precise and negative coefficients on upstreamness for both tariffs and NTBs. This sign is consistent with predictions from the model in which politicians choose lower tariffs on upstream goods because downstream firms lobby for low tariffs on inputs. The magnitude of the constant and the upstream coefficient represent the inverse of the weight that politicians put on social welfare versus campaign contributions. For example, the estimate of 4.55 for the constant in Panel B implies that politicians would trade off \$4.55 cents of campaign contributions for a dollar of social welfare. The regressions similarly imply that politicians would trade off about the same amount for campaign contributions from upstream firms. This mirrors findings for the U.S. in Gawande et al. (2012), though using different data, and suggests that a dollar of campaign contributions has the same value regardless of which industry supplies it.

This model analyzes a simple measure of upstreamness, equal to the share of an industry's output sold to other firms rather than final consumers. Appendix Table 6, column 2, shows similar conclusions come from the full upstreamness of Antràs et al. (2012). Relative likelihood tests based on the Akaike information criterion (AIC) imply that column 1 provides a marginally better fit to the data.

Appendix Table 6, column 3 replaces the upstreamness variable an industry's CO_2 intensity. This is not consistent with the model, but reflects the idea explored earlier that CO_2 intensity superficially seems important in trade policy because it is strongly correlated with upstreamness. The negative coefficient on CO_2 intensity appears consistent with the idea that politicians prefer lower tariffs on CO_2-intensive industries. The relative likelihood test implies that this estimate fits the data significantly less well than columns 1 and 2.

Appendix Table 6, columns 4 and 5, simultaneously consider information on both CO_2 intensity and upstreamness. In both cases, the coefficient on upstreamness is virtually unchanged upon controlling for CO_2 (i.e., columns 1 and 4 have similar upstreamness coefficients; columns 2 and 5 do also). Additionally, controlling for upstreamness renders the coefficient on CO_2 statistically insignificant and shrinks its magnitude by about 90 percent. Controlling for CO_2 in addition to the simple measure of upstreamness either does not significantly change or worsens the model fit.

C Model Equilibrium and Counterfactuals

The model assumptions give rise to several conditions which describe a competitive equilibrium. In other words, a set of prices and quantities which satisfies these equations is the result of consumer utility maximization, firm profit maximization, and market clearing. The first describes the cost to produce one unit of output:

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

This unit cost is Cobb-Douglas in the price of factors w_i and intermediates, and also Cobb-Douglas across the price index of intermediates P_{ik}. This follows from the production structure.

Sector s in country j then has the following price index, where $\delta_s = 1$ indexes the market structure of monopolistic competition and $\delta_s = 0$ for perfect competition:

$$P_{js} = \left(\sum_i (\phi_{ijs})^{-\theta_s} (c_{is})^{-\theta_s - \frac{\theta_s \delta_s}{\sigma_s - 1}} (X_{js})^{\delta_s \left(\frac{\theta_s}{\sigma_s - 1} - 1\right)} (R_{is})^{\delta_s} (\xi_{ijs})^{1-\sigma_s} \right)^{-\frac{1}{\theta_s}}$$

Here the price index depends on trade barriers $\phi_{ijs} \equiv \tau_{ijs}(1 + t_{ijs})(1 + n_{ijs})$, unit costs c_{is}, country×sector expenditure X_{js}, country×sector revenue R_{is}, and a combination of parameters and entry costs ξ_{ijs}. Here the parameter $\eta_s \equiv \frac{\theta_s}{\sigma_s - 1} - 1$ indexes firm heterogeneity. I treat NTBs n_{ijs} as a multiplicative tariff with revenue that is lost (or, equivalently, as a multiplicative form of iceberg trade cost).

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

$$\lambda_{ijs} = \frac{(\phi_{ijs})^{-\theta_s} (c_{is})^{-\theta_s - \frac{\theta_s \delta_s}{\sigma_s - 1}} (R_{is})^{\delta_s} (\xi_{ijs})^{1-\sigma_s}}{\sum_o \phi_{ojs}^{-\theta_s} (c_{os})^{-\theta_s - \frac{\theta_s \delta_s}{\sigma_s - 1}} (R_{os})^{\delta_s} (\xi_{ojs})^{1-\sigma_s}}$$

This is a standard gravity equation.

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

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

Revenues for a given country and sector equal pre-tariff bilateral trade, summed over destinations, and scaled since I assume tariffs are imposed on marginal costs but not markups:

$$R_{is} = \sum_j \left(1 + \frac{t_{ijs}}{\sigma_s}\right)^{\delta_s} \frac{\lambda_{ijs}}{1 + t_{ijs}} X_{js}$$

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

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

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

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

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

$$\hat{\lambda}_{ijs} = \frac{(\hat{\phi}_{ijs})^{-\theta_s} (\hat{c}_{is})^{-\theta_s - \frac{\theta_s \delta_s}{\sigma_s - 1}} (\hat{R}_{is})^{\delta_s}}{\left(\sum_i \lambda_{ijs} (\hat{\phi}_{ijs})^{-\theta_s} (\hat{c}_{is})^{-\theta_s - \frac{\theta_s \delta_s}{\sigma_s - 1}} (\hat{R}_{is})^{\delta_s}\right)^{-\frac{1}{\theta_s}}}$$

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

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

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

$$\hat{R}_{is} R_{is} = \sum_j \left(1 + \frac{t'_{ijs}}{\sigma_s}\right)^{\delta_s} \frac{\hat{\lambda}_{ijs} \lambda_{ijs}}{1 + t'_{ijs}} \hat{X}_{js} X_{js}$$

Finally, the change in national income is

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

I note two additional issues. First, the main text describes the choice of trade elasticities. Estimates under monopolistic competition with heterogeneous firms require a second elasticity, $\eta_s \equiv \frac{\theta_s}{\sigma_s - 1} - 1$. Following Balistreri et al. (2011) and Costinot and Rodriguez-Clare (2014), I impose $\eta_s = 0.65 \ \forall s$. A second issue involves calculation of equilibria. In addition to testing sensitivity to algorithms in Appendix Table 7, I re-calculate each equilibrium using random vectors of starting values. For estimates with perfect competition, these alternative starting values produce numerically equal results to the main estimates. For estimates with monopolistic competition, these alternative starting values in some cases identify local minima that are not numerically equivalent to the main estimates, though are in the same quantitative range as the main estimates. For all estimates under models of monopolistic competition, I hence re-estimate each equilibrium 200 times, each time using an independent draw of a vector of starting values drawn from the uniform distribution over [0.9,1.1]. I choose this distribution since it spans most counterfactual results and since some starting values well outside this range fail to converge. I exclude any of these estimates that fail to converge. I take the estimate with the lowest value of the objective function.

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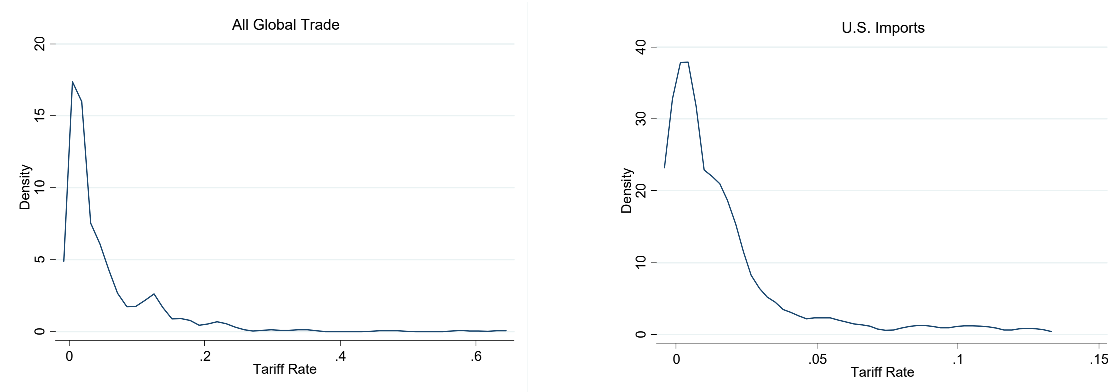
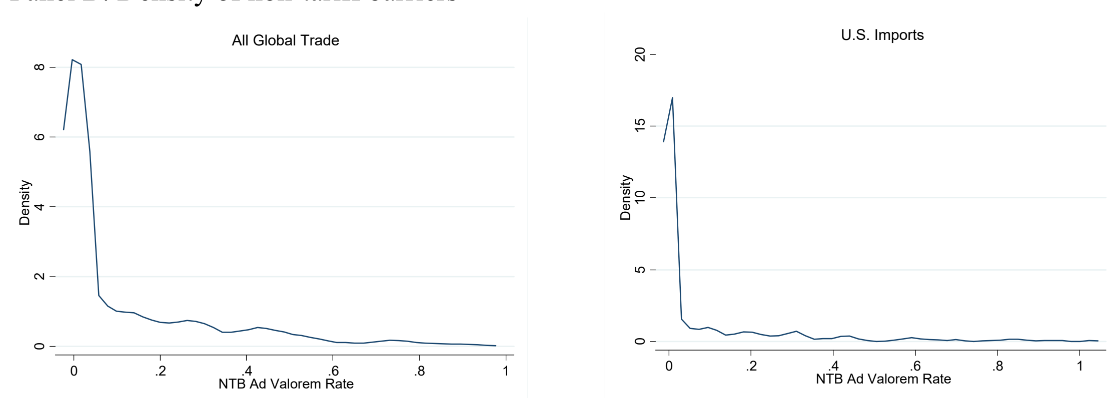
Appendix Figure 1—Densities of Trade Policy, Carbon Intensity, and Upstreamness

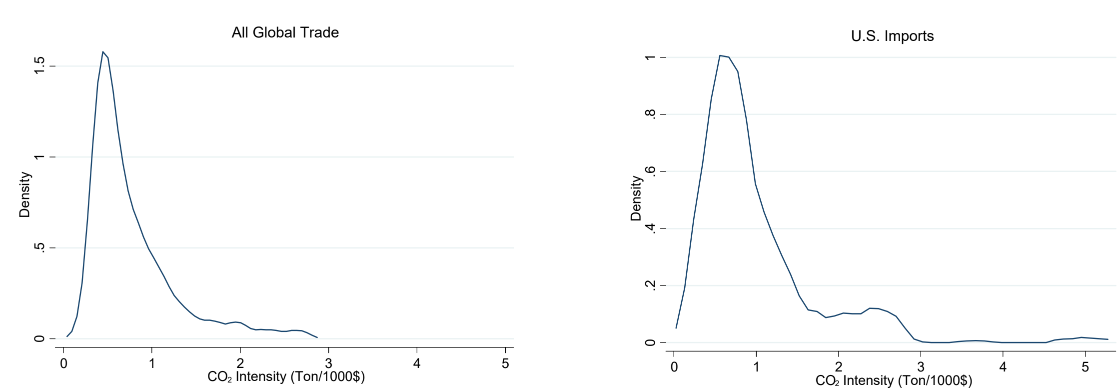
Panel A. Density of tariffs



Panel B. Density of non-tariff barriers



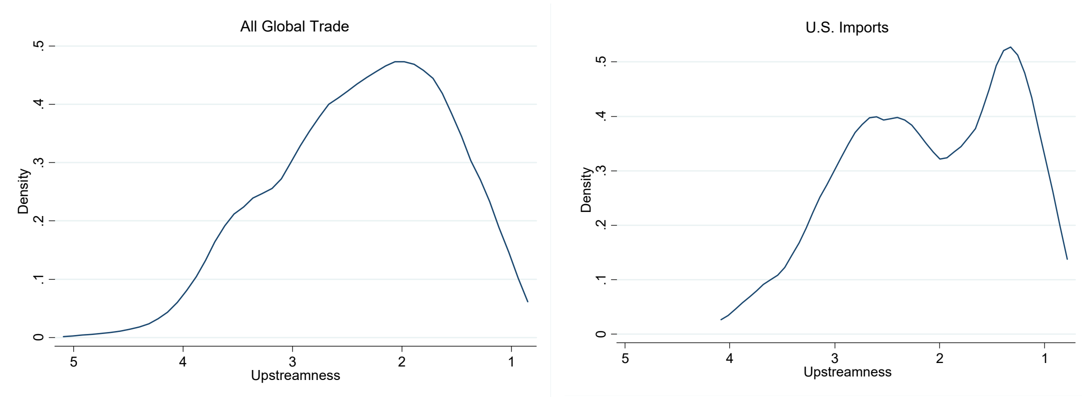
Panel C. Density of Total CO_2 intensity



(Continued on next page)

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

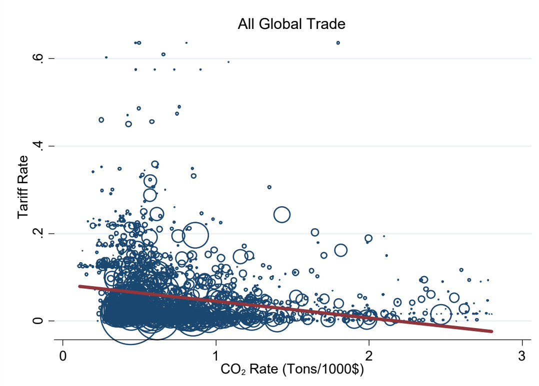
Panel D. Density of upstreamness

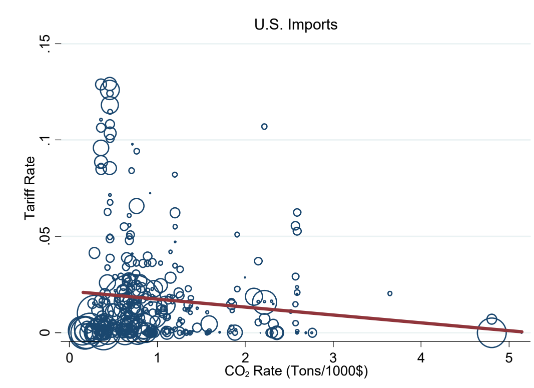


Notes: Graphs exclude top 1% of each variable. The value 5 represents the most upstream, while 1 is the least upstream. Upstreamness measured as in Antràs et al. (2012).

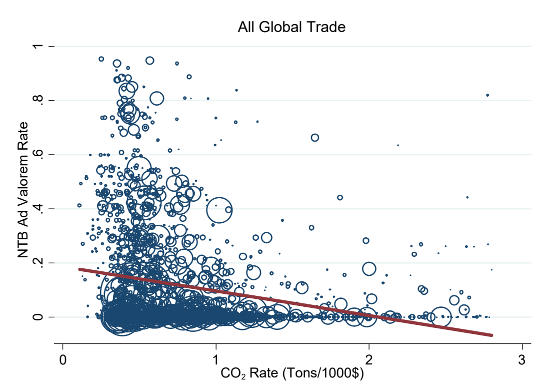
Appendix Figure 2—Trade Protection Versus CO_2 Emission Rates, Other Specifications

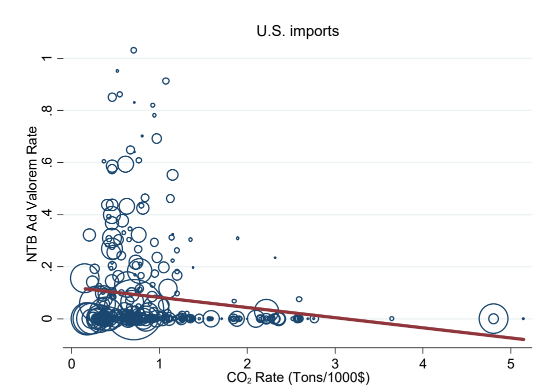
Panel A. Import tariffs, weighted



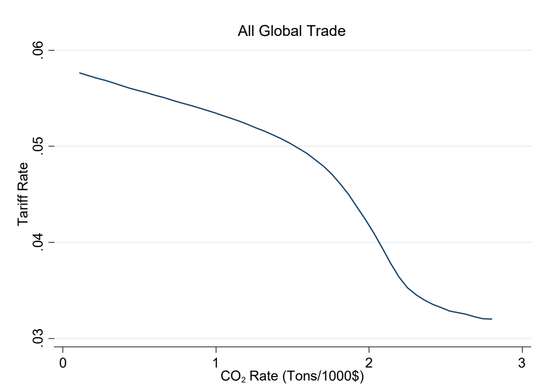


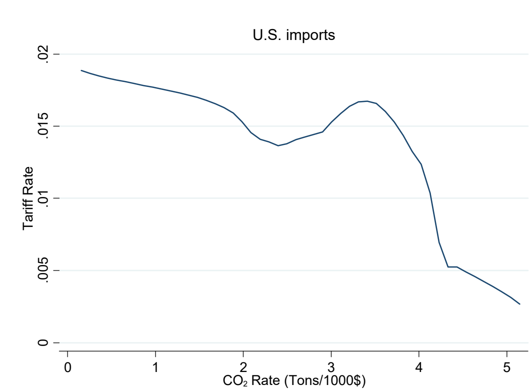
Panel B. Non-tariff barriers, weighted





Panel C. Import tariffs, nonparametric





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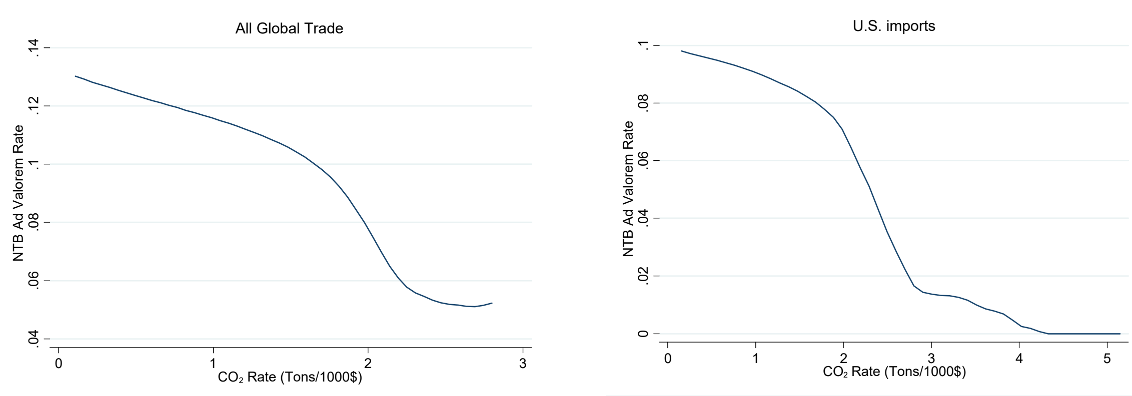
Appendix Figure 2—Trade Protection Versus CO_2 Emission Rates, Other Specifications (Continued)

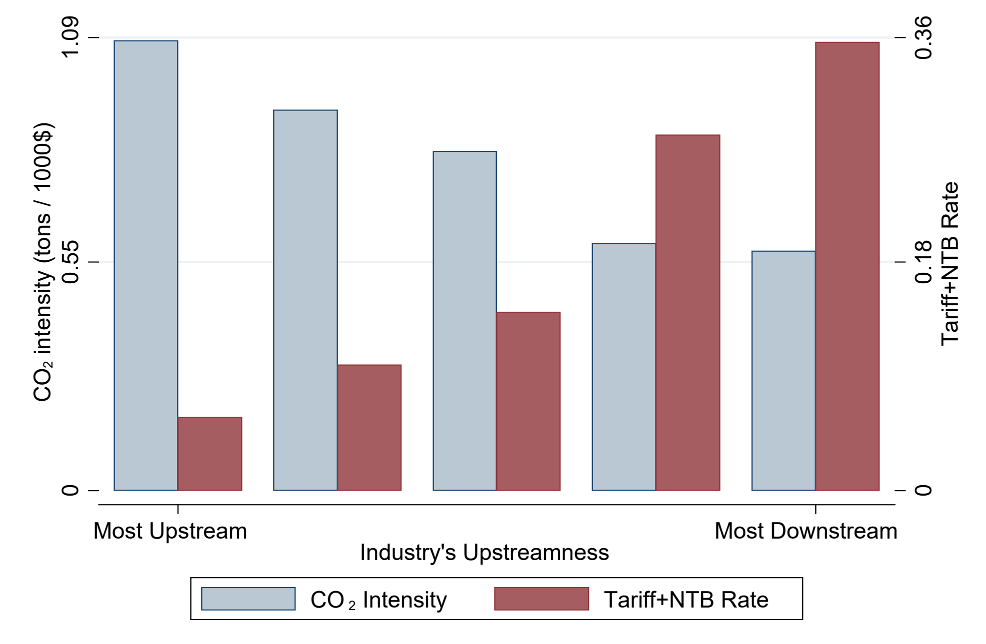
Panel D. Non-tariff barriers, nonparametric



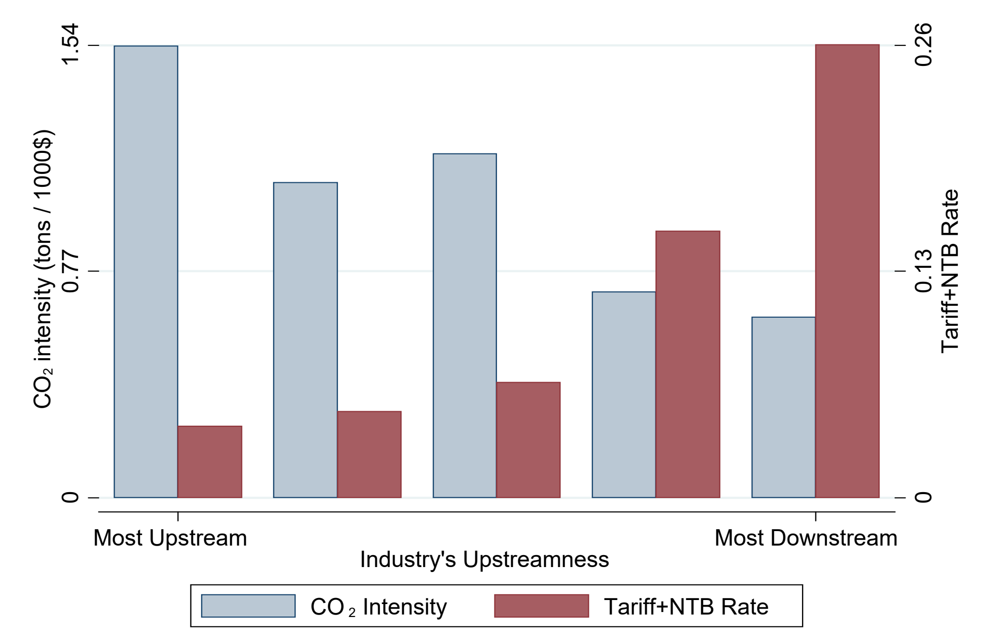
Notes: See notes to Figure 1. In weighted panels A and B, circle size is proportional to value of imports in each industry, and regression lines are weighted. Graphs exclude top 1% of each variable (CO_2, NTB, tariffs). Panels C and D use bandwidth of 0.75.

Appendix Figure 3—Upstream Location, CO_2 Intensity, and Tariff Rates, Bar Graph

Panel A. Global Data

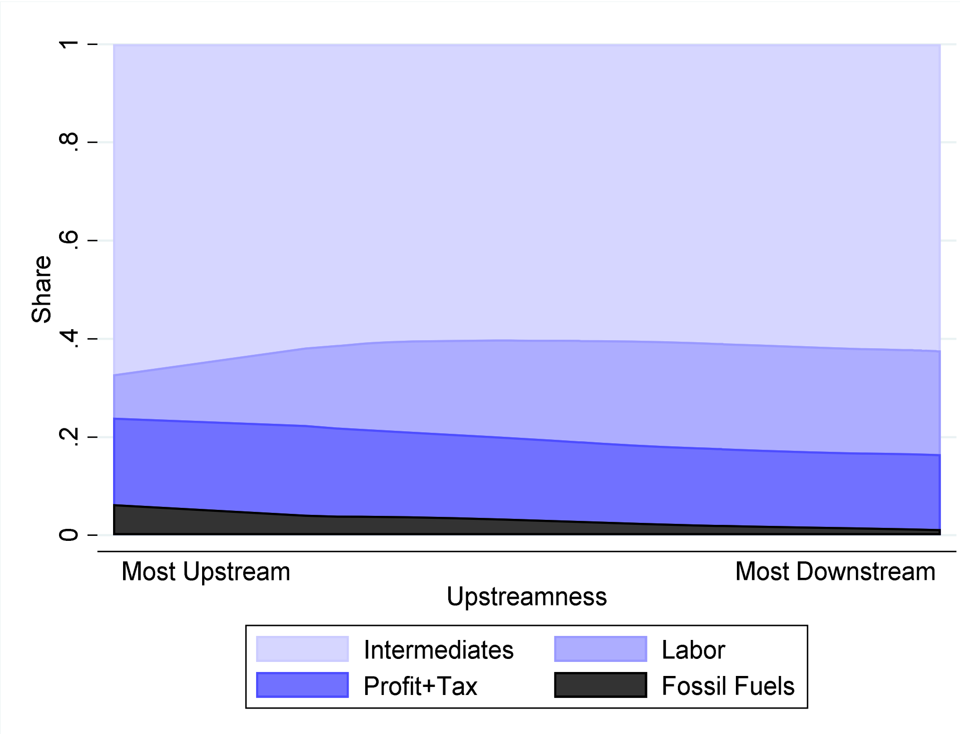


Panel B. U.S. Data



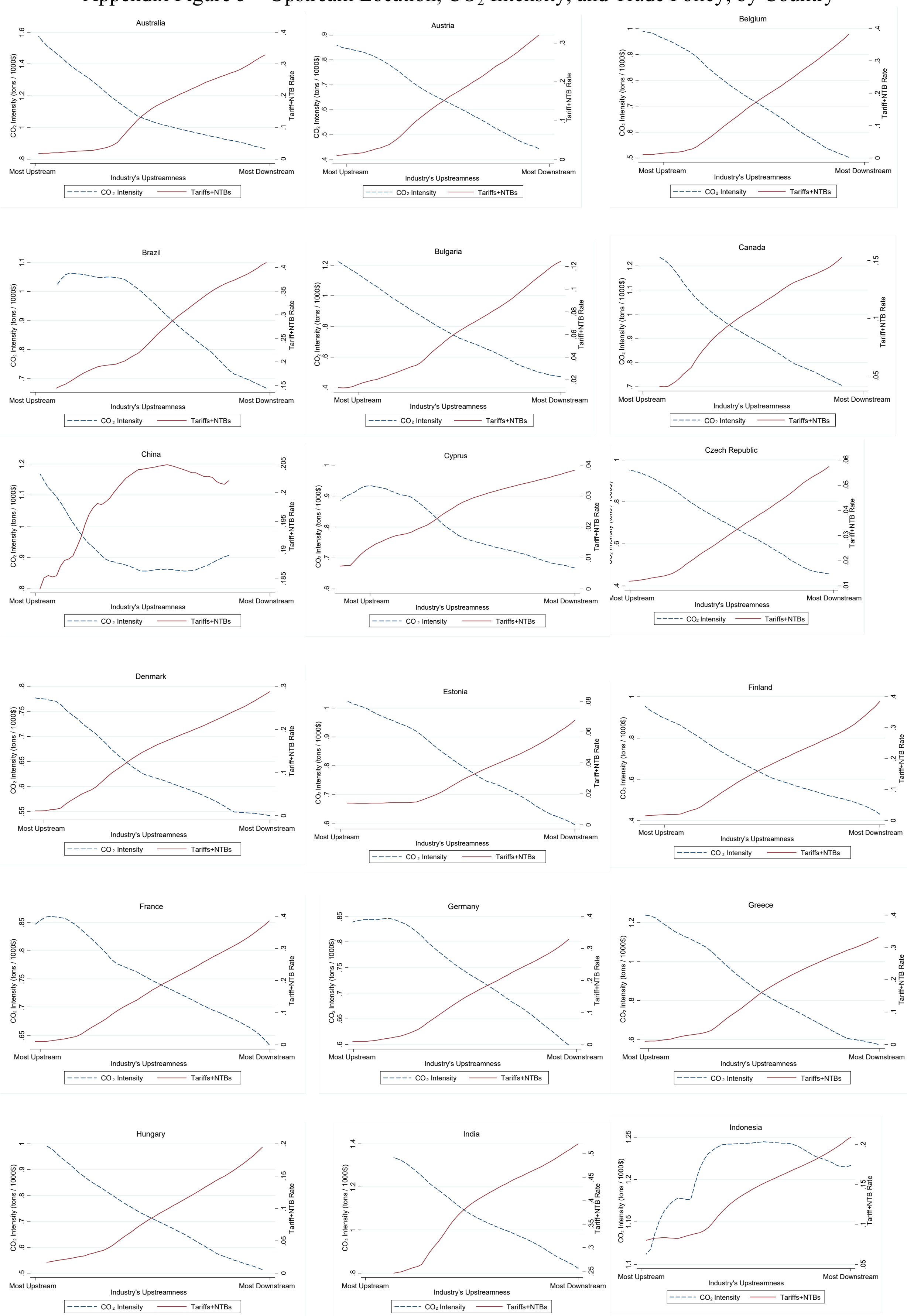
Notes: U.S. data for year 2007. Bar graph presents same data as Figure 6 but in different graphical format.

Appendix Figure 4—U.S. Upstreamness and Components of Revenues

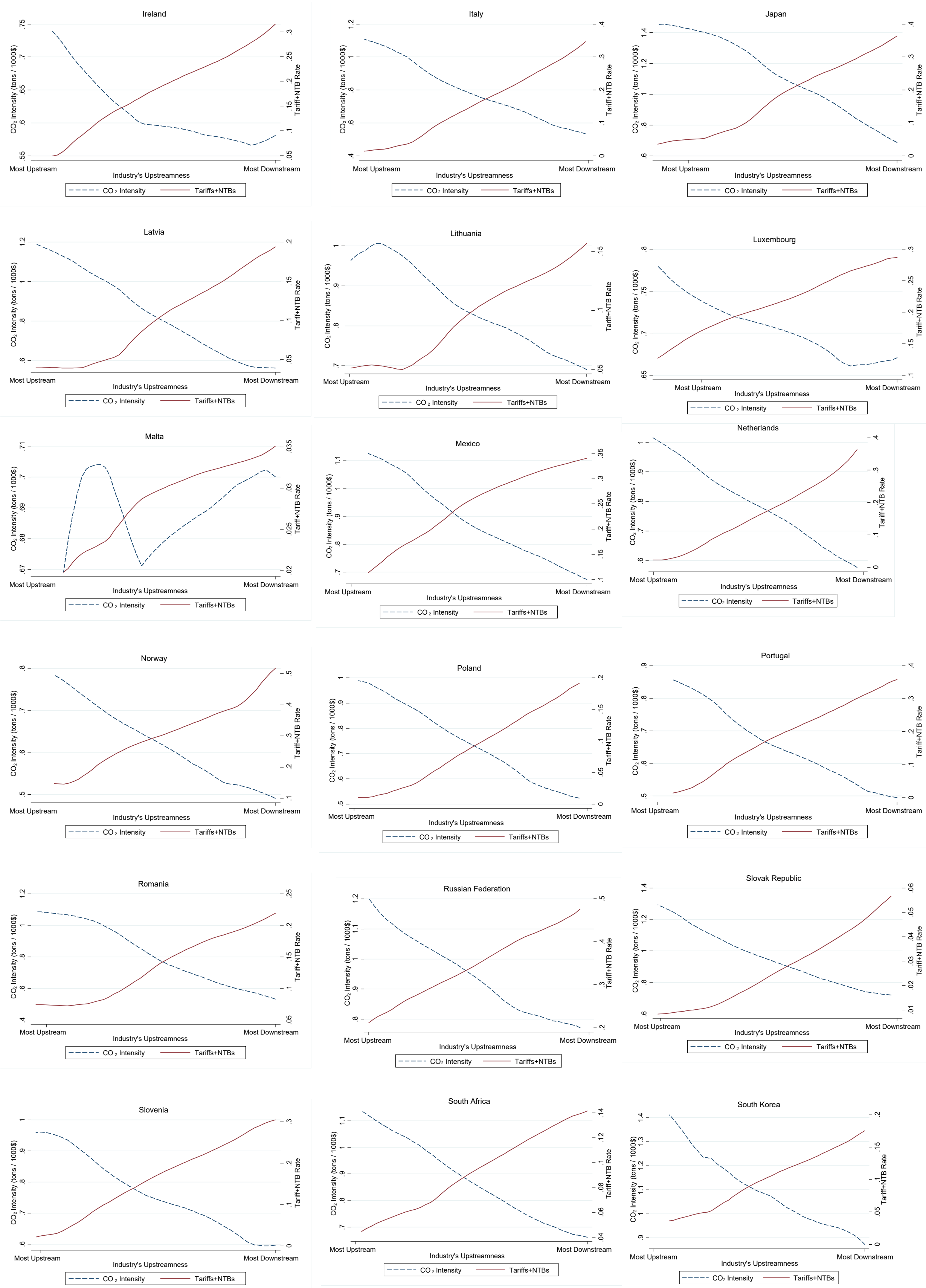


Notes: Data from the U.S. BEA use table for year 2007. Fossil fuel industries include natural gas distribution, oil and gas extraction, electricity generation, petroleum refineries, and coal mining. For smoothness, for each component of output separately, this analysis estimates a local linear regression 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).

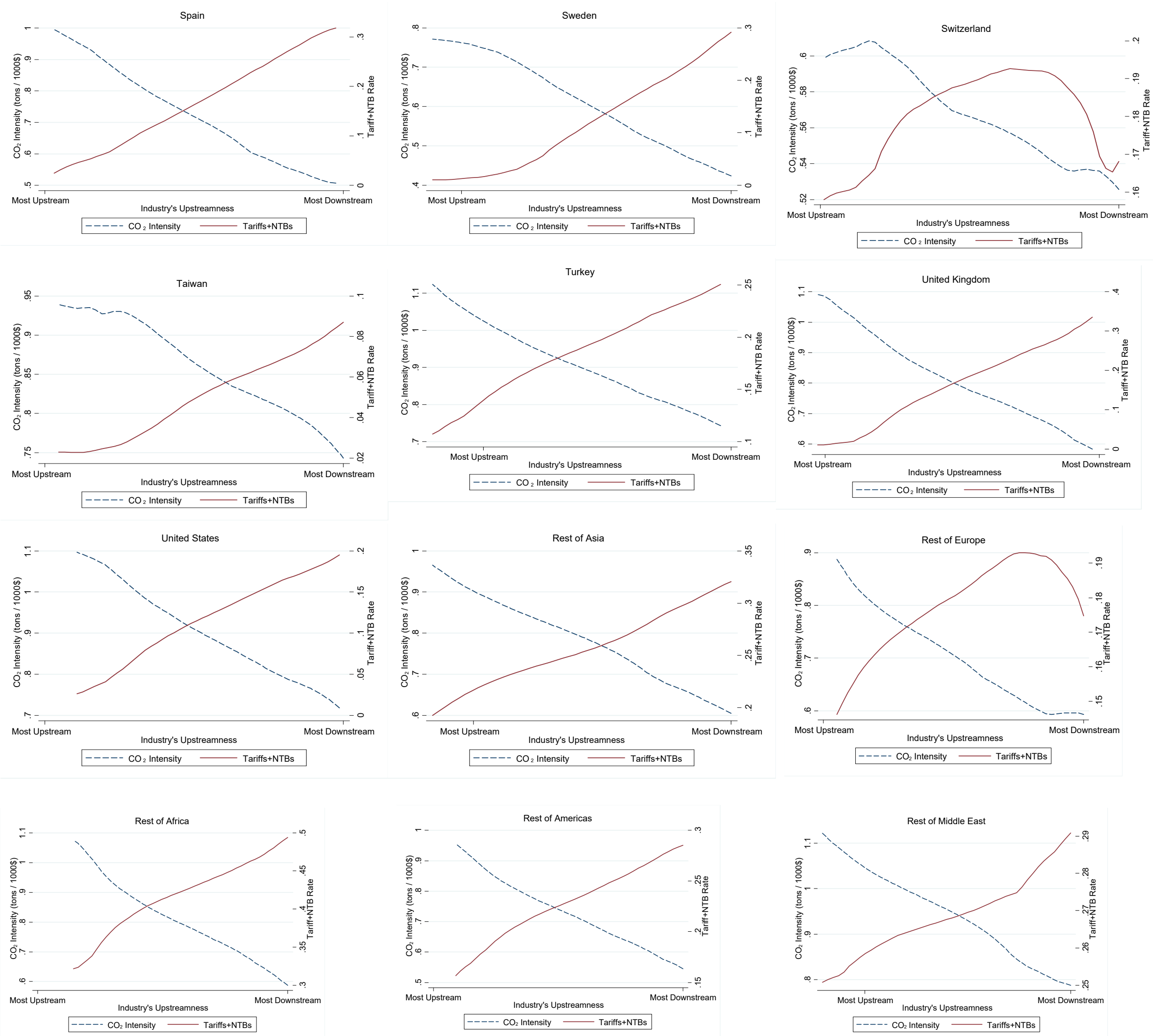
Appendix Figure 5—Upstream Location, CO_2 Intensity, and Trade Policy, by Country



Appendix Figure 5—Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)



Appendix Figure 5—Upstream Location, CO_2 Intensity, and Tariff Rates, by Country (Continued)



Note: 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.

Appendix Table 1—Potential Explanations for Implicit CO_2 Subsidies, U.S. Data

Category (1)	Variable (2)	Reason, source (3)	Data source (4)
Optimal tariffs	Inverse export supply elasticity	Terms of trade arguments (Bickerdike 1907)	Broda, Limao, and Weinstein (2008)
Demand for low protection from an industry's customers	Upstreamness	Downstream firms lobby for low tariffs on upstream suppliers (Gawande et al. 2012)	BEA detailed input-output table after redefinitions
	Intra-industry trade $1 - \|x_i - m_i\|/(x_i + m_i)$	Exporters concerned about retaliatory foreign tariffs (Marvel and Ray 1987)	Imports, Exports of Merchandise
Demand for protection from an industry	Output trends, 1972-2002	Rent protection (Baldwin and Robert-Nicoud 2007; Freund and Ozden 2008)	NBER-CES database
	Log import penetration ratio (imports / output)	Greater benefits from protection (Anderson 1980; Trefler 1993)	NBER-CES, Imports of Merchandise
	Log import penetration ratio trends 1997-2002	Greater incentive to lobby (Trefler 1993)	NBER-CES, Imports of Merchandise
	Labor share (workers / output)	More workers to benefit (Caves 1976)	NBER-CES database
	Workers: share with some college (%)	Equity, redistribution (Caves 1976; Anderson 1980)	May 2007 Current Population Survey (CPS)
	Workers: mean wage	Equity, redistribution (Caves 1976; Anderson 1980)	May 2007 CPS ASEC
Supply of lobbying or protection from an industry	Four-firm concentration ratio	Easier for concentrated industries to support lobbying (Caves 1976; Bombardini 2008)	Economic Census
	Mean firm size	Easier for few large firms to support lobbying (Bombardini 2008)	Economic Census
	Standard deviation of firm size	Easier for few large firms to support lobbying (Bombardini 2008)	Economic Census
	Capital share (capital stock / output)	Capital intensity determines trade flows, comparative advantage, concentration (Ray 1991)	NBER-CES
	Shipping cost per dollar*kilometer	Decreases import penetration ratio and concentration (Caves 1976)	Imports of Merchandise, CEPII
	Geographic dispersion (entropy across states)	Decreases concentration (Trefler 1993)	County Business Patterns
	Workers: unionized (%)	Unions lobby directly (Trefler 1993)	CPS (Hirsch and MacPherson 2003)
	Workers: unemployment	Disadvantaged groups have lower opportunity cost of lobbying (Trefler 1993)	CPS
	Political Action Committee contributions	Proxy for lobbying	Center for Responsive Politics

Appendix Table 2—Carbon Taxes Implicit in Trade Policy, Sensitivity Analysis

	Global		US Imports	
	Tariffs	NTBs	Tariffs	NTBs
	(1)	(2)	(3)	(4)
1. Main estimates	-18.06***	-72.17***	-7.08***	-36.49***
	(3.08)	(11.29)	(2.72)	(12.35)
<u>Other econometrics</u>				
2. Tobit (no instrument)	-20.75***	-146.00***	-3.43***	-147.61***
	(3.24)	(23.91)	(1.25)	(47.60)
3. Tobit (instrumented)	-18.11***	-127.83***	-10.84***	-307.02**
	(3.06)	(25.78)	(3.77)	(154.03)
4. Standard errors clustered	-18.06***	-72.17***	—	—
by importer	(2.63)	(13.29)	—	—
<u>Other data cleaning and aggregation</u>				
5. Winsorize dependent and	-18.27***	-73.64***	-6.83***	-36.25***
independent variables	(3.14)	(11.64)	(2.62)	(12.28)
6. Aggregate to 10 regions,	-36.88***	-156.87***	0.15	-0.37
21 industries	(9.15)	(42.34)	(0.59)	(2.67)
7. Include non-manufacturing	-14.95***	-56.20***	—	—
industries	(2.73)	(10.26)	—	—
8. Multiple trading partners	-4.29***	-28.28***	-7.08***	-36.49***
(i×j×s level data)	(1.04)	(2.49)	(1.43)	(6.03)
9. Multiple trading partners	-11.32***	-68.28***	0.15	-2.21
10 regions, 21 industries	(2.45)	(9.70)	(0.37)	(3.31)
10. Industry-level data	-22.63**	-80.94**	—	—
	(8.59)	(34.49)	—	—
<u>Additional sensitivity analyses</u>				
11. Lifecycle tariffs	-29.36**	-80.81***	—	—
	(11.61)	(25.90)	—	—
12. No importer fixed effects	-12.41**	-71.86***	—	—
	(6.05)	(11.74)	—	—
13. WIOD, not Exiobase	-12.55**	-106.86***	—	—
	(6.02)	(21.18)	—	—

(Continued on next page)

Appendix Table 2—Carbon Taxes Implicit in Trade Policy, Sensitivity Analysis (continued)

	Global		US Imports	
	Tariffs	NTBs	Tariffs	NTBs
	(1)	(2)	(3)	(4)
14. Include all greenhouse gases,	-17.35***	-69.22***	—	—
process emissions	(2.95)	(10.90)	—	—
15. Exclude manufactured food,	-11.02***	-40.64***	-7.25***	-35.43***
manufactured agricultural goods	(2.72)	(8.58)	(2.78)	(11.95)

Notes: All regressions are instrumental variables estimates weighted by the value of the trade flow and correspond to Tables 2-3, column 5, except where otherwise noted. All regressions include a constant. Parentheses show robust standard errors except in row 4. In columns 3 and 4, hyphens indicate data which are same as row 1 or which are not available for U.S. imports only (e.g., MECS survey does not cover non-manufacturing; WIOD v. Exiobase not relevant for U.S. microdata; all greenhouse gases not separately reported). Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 3—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	-8.20***	-6.25**	-75.59***	-62.07**
	(2.37)	(2.63)	(15.05)	(28.61)
N	382	382	382	382
Dep. Var. Mean	0.030	0.020	0.322	0.289
Panel B. Japanese import tariffs				
CO_2 rate	-58.93***	-49.13*	-66.29***	-41.91
	(17.92)	(28.12)	(19.25)	(25.68)
N	47	47	47	47
Dep. Var. Mean	0.084	0.044	0.09	0.046
Panel C: Chinese import tariffs				
CO_2 rate	8.37	23.67	-161.29**	-143.42*
	(13.53)	(17.61)	(63.32)	(83.86)
N	47	47	47	47
Dep. Var. Mean	0.100	0.068	0.601	0.491
Weighted		X		X

Note: 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. Robust standard errors in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All global trade, weighted						
CO_2 rate	-90.11***	-25.47	-90.23***	-90.13***	-90.10***	-92.34***
	(11.95)	(15.82)	(11.98)	(11.95)	(11.96)	(12.89)
Panel B. All global trade, instrument for political economy, weighted						
CO_2 rate	-90.11***	0.46	-90.17***	-90.76***	-90.55***	-95.04***
	(11.95)	(20.00)	(11.93)	(11.96)	(12.97)	(13.45)
K-P F Statistic	—	307.4	82.5	0.9	12.9	227.9
Panel C. U.S. imports, weighted						
CO_2 rate	-34.71***	2.34	-31.49**	-29.55***	-28.49***	-37.59***
	(11.32)	(12.80)	(12.41)	(10.92)	(10.78)	(11.44)
Panel D. U.S. imports, direct CO_2 only						
CO_2 rate	-63.43***	-5.47	-63.07***	-56.85***	-62.04***	-66.15***
	(18.75)	(12.31)	(18.92)	(17.27)	(19.51)	(19.08)
Panel E. U.S. imports, direct CO_2 only, weighted						
CO_2 rate	-81.68***	3.98	-73.90***	-67.93***	-61.45***	-88.99***
	(28.99)	(22.15)	(24.88)	(26.17)	(23.23)	(24.92)
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 all other countries.Panels A and B include country fixed effects. All regressions include a constant. Robust standard errors in parentheses. Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 5—Political Economy Explanations: All Controls Together

	All global trade			U.S. imports	
	IV	IV	Lasso	IV	Lasso
	(1)	(2)	(3)	(4)	(5)
CO_2 Intensity	-28.429***	-18.445	-28.018***	-70.365*	-4.815
	(7.661)	(33.233)	(7.673)	(38.341)	(10.218)
Upstreamness	-0.113***	-0.215***	-0.112***	-0.047***	-0.071***
	(0.005)	(0.026)	(0.005)	(0.013)	(0.014)
Intra-industry trade	-0.002	-0.034	0	-0.025**	0
	(0.005)	(0.036)	0	(0.012)	0
Import penetration ratio	0.058	-2.961	0	-0.028	0
	(0.036)	(3.272)	0	(0.023)	0
Labor share	-0.013***	-0.749***	0	-0.054***	0
	(0.005)	(0.220)	0	(0.020)	0
Workers: mean wage	0.003	0.276***	0	-0.035*	0
	(0.008)	(0.097)	0	(0.018)	0
Inverse export supply elast.	—	—	—	-0.003	0
				(0.007)	0
Output trends 1972-2002	—	—	—	-0.001	0
				(0.009)	0
Trend in import pen. Ratio	—	—	—	0.052**	0
				(0.025)	0
Workers: share w/ college	—	—	—	-0.015	0
				(0.019)	0
Four-firm conc. Ratio	—	—	—	-0.031*	0
				(0.016)	0
Mean firm size	—	—	—	0.076*	0
				(0.044)	0
Standard dev. of firm size	—	—	—	-0.082*	0
				(0.043)	0
Capital share	—	—	—	0.025	0
				(0.022)	0
Shipping cost per dollar*km	—	—	—	0.022	0
				(0.024)	0
Geographic dispersion	—	—	—	0.021	0
				(0.018)	0
Workers: unemployed	—	—	—	0.020	0
				(0.015)	0
Workers: unionized (%)	—	—	—	0.012	0
				(0.012)	0
PAC contributions	—	—	—	0.010	0
				(0.012)	0
Instrument Pol. Ec. Vars.		X			

Notes: Lasso entries of "0" mean the coefficient is exactly zero. CO_2 intensity refers to total intensity from the input-output table. Total CO2 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. Robust standard errors in parentheses.

Appendix Table 6—Model-Based Estimates: Lobbying Competition and Protection for Sale

	(1)	(2)	(3)	(4)	(5)
Panel A: Tariffs					
Upstream Location	-2.45***	-0.96***	—	-2.39***	-0.94***
	(0.68)	(0.27)	—	(0.67)	(0.27)
CO_2 rate	—	—	-493.94***	-56.82	-48.94
	—	—	(171.60)	(59.99)	(66.18)
Constant	2.16***	2.73***	1.18***	2.19***	2.73***
	(0.58)	(0.75)	(0.33)	(0.59)	(0.74)
p-value of H_0: upstream=constant	0.00	—	—	—	—
First Stage F (K-P)	—	—	38.6	38.9	39.1
AIC	1,874.2	1,879.8	1,891.7	1,875.9	1,881.6
Relative Likelihood	—	0.06	0.00	0.42	0.02
Panel B: Non-tariff barriers (ad valorem equivalent)					
Upstream Location	-5.06***	-2.04***	—	-4.97***	-2.02***
	(1.34)	(0.53)	—	(1.31)	(0.52)
CO_2 rate	—	—	-1009.41***	-104.02	-60.54
	—	—	(353.67)	(143.09)	(154.74)
Constant	4.55***	5.83***	2.51***	4.60***	5.83***
	(1.15)	(1.46)	(0.67)	(1.16)	(1.46)
p-value of H_0: upstream=constant	0.00	—	—	—	—
First Stage F (K-P)	—	—	38.7	38.8	39.1
AIC	2,341.2	2,346.4	2,360.8	2,342.9	2,348.3
Relative Likelihood	—	0.07	0.00	0.42	0.03
Upstreamness: Basic	X			X	
Upstreamness: Full		X			X

Notes: All estimates include U.S. imports for the year 2007. Robust standard errors in parentheses. Regressions in Panel A each have N=357 observations regressions in Panel B each have 355 observations. All regressions include a constant. CO_2 rate is calculated from inverting an input-output table, and is instrumented with direct CO_2 rate. Full upstreamness is from Antràs et al. (2012), basic upstreamness is share of output sold to firms (versus final consumers). Asterisks denote p-value * < 0.10, ** < 0.05, *** <0.01.

Appendix Table 7—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare, General Equlibrium Alternative Analyses

	CO_2 Emissions			Real Income			CO_2, Fix Income		
	EK (1a)	Krugman (1b)	Melitz (1c)	EK (2a)	Krugman (2b)	Melitz (2c)	EK (3a)	Krugman (3b)	Melitz (3c)
Panel A: Reform All Trade Policy									
1. Baseline estimates	-0.26%	-1.22%	-2.14%	0.89%	1.44%	1.16%	-1.15%	-2.66%	-3.29%
Decomposition									
2. Scale effect only	0.63%	1.67%	1.41%	—	—	—	—	—	—
3. Composition effect only	-0.35%	-0.79%	-0.92%	—	—	—	—	—	—
4. Technique effect only	-0.54%	-2.10%	-2.62%	—	—	—	—	—	—
Other data									
5. WIOD, not Exiobase	-0.11%	-1.66%	-0.85%	0.94%	1.34%	1.25%	-1.05%	-3.00%	-2.09%
6. All GHG, not just CO2	-0.22%	-1.07%	-1.86%	0.89%	1.44%	1.16%	-1.11%	-2.51%	-3.01%
7. Trade elasticities: Caliendo-Parro	-0.09%	-0.56%	-3.75%	0.63%	1.31%	1.02%	-0.71%	-1.87%	-4.77%
Other counterfactuals									
8. Harmonize within importer	-0.31%	-1.15%	-1.65%	0.87%	0.91%	0.93%	-1.17%	-2.06%	-2.57%
9. Harmonize tariffs only	0.09%	0.29%	0.11%	0.14%	0.19%	-0.30%	-0.05%	0.09%	0.40%
10. Harmonize NTBs only	-0.55%	-0.35%	-1.11%	0.64%	0.90%	0.74%	-1.19%	-1.25%	-1.85%
Other estimation methods									
11. First remove trade deficits	-0.24%	-1.18%	-0.31%	0.89%	1.46%	1.16%	-1.13%	-2.64%	-1.47%
12. Algorithm: trust-region	-0.26%	-1.22%	-2.14%	0.89%	1.44%	1.16%	-1.15%	-2.66%	-3.29%
13. Algorithm: Levenberg-Marquardt	-0.26%	-1.22%	-2.14%	0.89%	1.44%	1.16%	-1.15%	-2.66%	-3.29%

(Continued next page)

Appendix Table 7—Effects of Counterfactual Tariffs and NTBs on CO_2 Emissions and Welfare
General Equilibrium Alternative Analyses (Continued)

	CO_2 Emissions			Real Income			CO_2, Fix Income		
	EK (1a)	Krugman (1b)	Melitz (1c)	EK (2a)	Krugman (2b)	Melitz (2c)	EK (3a)	Krugman (3b)	Melitz (3c)
<u>Panel B: Reform Manufacturing Trade Policy</u>									
1. Baseline estimates	0.12%	-0.95%	0.53%	1.11%	1.63%	1.32%	-0.99%	-2.57%	-0.79%
Decomposition									
2. Scale effect only	0.88%	1.83%	1.17%	—	—	—	—	—	—
3. Composition effect only	-0.31%	-0.72%	-0.35%	—	—	—	—	—	—
4. Technique effect only	-0.45%	-2.06%	-0.29%	—	—	—	—	—	—
Other data									
5. WIOD, not Exiobase	-0.36%	0.19%	-3.36%	0.58%	0.55%	-1.09%	-0.94%	-0.37%	-2.26%
6. All GHG, not just CO2	0.13%	-0.91%	0.47%	1.11%	1.63%	1.32%	-0.98%	-2.54%	-0.85%
7. Trade elasticities: Caliendo-Parro	0.30%	0.95%	-0.91%	0.88%	1.55%	1.52%	-0.58%	-0.61%	-2.43%
Other counterfactuals									
8. Harmonize within importer	0.23%	-1.21%	0.54%	1.18%	1.24%	1.77%	-0.95%	-2.45%	-1.23%
9. Harmonize tariffs only	0.06%	-0.28%	-0.27%	0.12%	0.14%	0.07%	-0.06%	-0.42%	-0.33%
10. Harmonize NTBs only	-0.10%	-1.49%	-2.44%	0.90%	0.63%	1.32%	-1.00%	-2.12%	-3.76%
Other estimation methods									
11. First remove trade deficits	0.13%	-1.06%	0.46%	1.11%	1.67%	1.33%	-0.98%	-2.73%	-0.87%
12. Algorithm: trust-region	0.12%	-0.95%	0.53%	1.11%	1.63%	1.32%	-0.99%	-2.57%	-0.79%
13. Algorithm: Levenberg-Marquardt	0.12%	-0.95%	0.53%	1.11%	1.63%	1.32%	-0.99%	-2.57%	-0.79%

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

Appendix Table 8—Country Aggregation in General Equilibrium Model

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

Appendix Table 9—Sectors and Trade Elasticities

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