Greening Ricardo: Environmental Comparative Advantage and the Environmental Gains From Trade *

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Abstract

We show that climate policy can unlock large environmental gains from trade by inducing countries to specialize according to their environmental comparative advantage. We make this point by exploring the effects of a carbon tax in a quantitative trade model. Our main result is that the environmental gains from trade account for over one-third of the total reduction in greenhouse gas emissions brought about by the carbon tax. This finding holds for a wide range of carbon tax rates and coverages.

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1 Introduction

In this paper, we show that climate policy can unlock large environmental gains from trade by inducing countries to specialize according to their environmental comparative advantage. The main idea is that global greenhouse gas emissions fall when countries specialize in industries where they have relatively low emissions, just like global real incomes rise when countries specialize in industries where they have relatively high productivity. While our notion of environmental comparative advantage therefore builds directly on the classic idea of economic comparative advantage, it has so far been largely absent from the trade and climate change debate.

This matters, since our results provide a strong counterpoint to the widespread view that international trade is an obstacle in the fight against climate change. While it is true that international trade causes transport emissions, our analysis shows that it can also be a powerful tool to reduce production emissions, which account for the lion's share of total emissions associated with traded goods. More broadly, it also offers a more inclusive perspective on sustainable development by highlighting that countries do not need to sacrifice the economic gains from trade in the name of climate stewardship but can pursue both objectives concurrently.

We make this point by exploring the effects of a carbon tax in a multi-country, multi-industry quantitative trade model with input-output linkages, calibrated to 64 regions and 45 industries spanning the world economy. Our benchmark scenario is a uniform carbon tax of \$100/tCO2eq on all goods in all countries, but our main result holds for a wide range of carbon tax rates and coverages. In this paper, we do not model how greenhouse gas emissions cause climate change, or how climate change affects economic activity. While these are important considerations, they are not essential for measuring the environmental gains from trade.[1]

[1] Well-known examples of integrated assessment models capturing these considerations include Nordhaus (1993), Nordhaus (2018), Golosov et al. (2014), and Boyce (2018).

Our main result is that the environmental gains from trade account for more than one-third of the greenhouse gas emissions reductions brought about by the carbon tax. This result holds for a wide range of carbon tax rates and coverages thus suggesting that trade is a strong force multiplier for climate policy. Moreover, we find that increases in carbon tax rates – even extreme ones up to \$1,000/tCO_2e - leave the volume of world trade relative to world gross production largely unchanged. This further corroborates the point that trade is part of the solution no matter how ambitious climate action becomes.

To isolate the environmental gains from trade, we decompose the greenhouse gas emissions reductions brought about by the carbon tax into three effects: (i) a reduction in the scale of global production (scale effect), (ii) a shift in economic activity towards greener sectors (composition effect), and (iii) a shift in economic activity towards greener countries (green sourcing effect). While the scale and composition effects also operate in a closed economy, the green sourcing effect exploits a margin that is only available with international trade and thus captures the environmental gains from trade. We hold emissions intensities fixed in our analysis so there is no technique effect.[2]

To the best of our knowledge, we provide the first estimate of the environmental gains from trade driven by environmental comparative advantage. We make this contribution leveraging well-known methods at the intersection of international and environmental economics. In particular, we use a standard quantitative trade model in the spirit of Caliendo and Parro (2015) and employ a variation of the familiar decomposition of greenhouse gas emissions changes into scale, composition, and technique effects dating back to Grossman and Krueger (1991). Hence, the novelty of our paper does not lie in the tools we develop but in the perspective we provide on the relationship between international trade and climate change.

Our paper follows in the footsteps of the pioneering work by Shapiro (2016), who spear-

[2]We are measuring the static environmental gains from trade. There may be additional dynamic environmental gains from trade, for example, if market size effects accelerate the green innovation spurred by carbon taxes.

headed the use of modern quantitative trade models in environmental economics. His main result is that international trade brings economic gains and emissions costs relative to autarky, with the economic gains far exceeding the emissions costs. We are approaching the issue from a different angle, essentially simulating the first-best pattern of trade, once environmental externalities are internalized by a carbon tax.

Our paper also has points of contact with the recent work by Farrokhi and Lashkaripour (2021), who explore to what extent trade policy can help solve the free-rider problem in international climate agreements. Their main finding is that a climate club could be highly effective, whereas border carbon adjustments have minimal impact. As part of this exercise, the authors also characterize optimal carbon taxes under various assumptions about international cooperation. In contrast, we do not derive optimal policy but simply examine the implications of a range of exogenous carbon tax regimes on greenhouse gas emissions and trade.

A closely related theme that has received much attention in the literature is carbon leakage[3]. The concern is that unilateral carbon measures in relatively green countries can lead to the relocation of emissions-intensive industries to relatively brown countries. The green sourcing effect identified in this paper essentially reverses this type of carbon leakage. However, it is important to keep in mind that a carbon tax induces specialization according to environmental comparative advantage, meaning that the adjustments extend beyond simple green sourcing in general equilibrium. One implication is that even the brownest country is contributing to reducing greenhouse gas emissions by moving resources to its relatively low emissions sectors.

The remainder of the paper is structured as follows. Section 2 sketches the model and decomposition, Section 3 turns to the data and calibration, and Section 4 presents the results.

[3]See, for example, Felder and Rutherford (1993); Larch and Wanner (2017); Kortum and Weisbach (2021).

2 Model

2.1 Setup

We work with a multi-country, multi-industry Armington (1969) model with input-output linkages. It is now well understood that such a model has the same aggregate predictions as the model of Caliendo and Parro (2015), which is based on the Ricardian model of Eaton and Kortum (2002).

There are N countries indexed by i (for origin) and j (for destination) and S industries indexed by s' (for upstream) and s (for downstream). Each country produces a unique variety within each industry and trade is subject to iceberg trade costs $\tau_{is'j} \geq 1$ with $\tau_{is'i} = 1$ for all i. Countries are endowed with an inelastic supply of workers L_i who are internationally immobile.

In our benchmark scenario, a uniform carbon tax is imposed on all goods in all countries. It is levied in the country of (final or intermediate) consumption and redistributed lump-sum to households in that country.[4] For our calculations, we convert it into an ad valorem tax $t^e_{is'}$ using emissions intensities. In particular, we calculate $t^e_{is'} = t * e_{is'}$, where t is the uniform carbon tax imposed on a ton of emissions and $e_{is'}$ are the emissions generated by the production of \$1 worth of industry s' output in country i. To avoid double counting, $e_{is'}$ captures only the emissions directly caused by the production process (e.g. the chemical reaction resulting in cement) but not the emissions caused indirectly by the use of inputs (e.g. the electricity used to power the cement factory).

[4] Given that the carbon tax is imposed on all goods in all countries, it is largely irrelevant whether it is imposed on consumers or producers. There are some differences in the cross-country allocation of tax revenues but they have negligible effects on our results. We find it easier to illustrate the relative price effects of the carbon tax with a consumption-based approach.

2.2 Equilibrium

Consumption choices are made by representative households with Cobb-Douglas-CES preferences

$$U_j = \prod_{s'} \left(U_{s'j}\right)^{\beta_{s'j}} \tag{1}$$

$$U_{s'j} = \left[\sum_i \left(a_{is'}\right)^{1/\sigma_{s'}} \left(q_{is'j}\right)^{(\sigma_{s'}-1)/\sigma_{s'}}\right]^{\sigma_{s'}/(\sigma_{s'}-1)}, \tag{2}$$

where $\beta_{s'j}$ are expenditure shares, $a_{is'}$ are demand shifters, $\sigma_{s'}$ are substitution elasticities, and $q_{is'j}$ are the final consumption quantities of varieties differentiated by country of origin. As a result, household final demand is given by

$$q_{is'j} = a_{is'} \frac{\left[p_{is'j}\left(1+t^e_{is'j}\right)\right]^{-\sigma_{s'}}}{\left(P^c_{s'j}\right)^{1-\sigma_{s'}}} \beta_{s'j} I_j \tag{3}$$

$$I_j = w_j L_j + R_j + D_j, \tag{4}$$

where $p_{is'j}$ are delivered prices, $P^c_{s'j}$ are consumer price indices, $w_j L_j$ is labor income, R_j is tax revenue, and D_j is an exogenous transfer used to match aggregate trade deficits in the data, which we keep constant in our counterfactuals. Notice that the carbon tax makes browner varieties more expensive thus inducing households to make greener consumption choices.

Firms produce these varieties under perfect competition from labor and intermediate goods using Cobb-Douglas-CES technologies

$$q_{js} = A_{js} \left(\frac{L_{js}}{\gamma_{j,L_s}}\right)^{\gamma_{j,L_s}} \prod_{s'} \left(\frac{m_{s'js}}{\gamma_{s'js}}\right)^{\gamma_{s'js}} \tag{5}$$

$$m_{s'js} = \left[\sum_i \left(b_{is'}\right)^{1/\eta_{s'}} \left(m_{is'js}\right)^{(\eta_{s'}-1)/\eta_{s'}}\right]^{\eta_{s'}/(\eta_{s'}-1)}, \tag{6}$$

where A_{js} are total factor productivities, $\gamma_{s'js}$ are cost shares, $b_{is'}$ are demand shifters, $\eta_{s'}$

are substitution elasticities, and $m_{s'js}$ are the intermediate consumption quantities of the same varieties also demanded by households. As a result, firm intermediate demand is given by

$$m_{is'js} = b_{is's} \frac{\left[p_{is'j}\left(1+t^e_{is'j}\right)\right]^{-\eta_{s'}}}{\left(P^p_{s'j}\right)^{1-\eta_{s'}}} \gamma_{s'js} E_{js}, \tag{7}$$

where $P^p_{s'j}$ are producer price indices. Notice that the carbon tax makes browner varieties more expensive thus inducing firms to make greener production choices.

We close the model by imposing labor and goods market clearing

$$\sum_s L_{js} = L_j \tag{8}$$

$$\underbrace{\sum_{s'} \sum_j p_{is'j} \left(q_{is'j} + \sum_s m_{is'js}\right)}_{\text{exports of } i} + D_i = \underbrace{\sum_{s'} \sum_j p_{js'i} \left(q_{js'i} + \sum_s m_{js'is}\right)}_{\text{imports of } i}. \tag{9}$$

To be clear, exports flow from upstream industries s' in country i to final consumers and downstream industries s in country j. Analogously, imports flow from upstream industries s' in countries j to final consumers and downstream industries s in country i. D_i is therefore equal to the trade deficit (or trade surplus if negative).

2.3 Decomposition

To help us understand the effect of carbon taxes on greenhouse gas (GHG) emissions, we develop a simple decomposition in the spirit of the scale-composition-technique effect decomposition familiar from the environmental economics literature. To this end, we define total trade flows $x_{is'j} \equiv p_{is'j}\left(q_{is'j} + \sum_s m_{is'js}\right)$ and write total emissions as $GHG = \sum_i \sum_j \sum_{s'} x_{is'j} e_{is'}$. Totally differentiating this expression holding emissions intensities constant, we decompose the overall change in emissions into a scale, composition, and green sourcing effect:

$$d\ln GHG = \underbrace{d\ln x}_{\text{scale effect}} + \underbrace{\sum_s \epsilon_s d\ln\alpha_s}_{\text{composition effect}} + \underbrace{\sum_i\sum_s \epsilon_{is} d\ln\alpha_{is}}_{\text{green sourcing effect}}, \tag{10}$$

where x is world expenditure, the α's are expenditure shares and the ϵ's are emissions shares. Specifically, α_s is the share of world expenditure flowing to industry s and α_{js} is the share of world expenditure on industry s flowing to country j. ϵ_s is the contribution of industry s to world emissions and ϵ_{js} is the contribution of industry s in country j to world emissions.[5]

Applied to our model, equation (10) captures that carbon taxes reduce emissions for three reasons. First, carbon taxes reduce aggregate expenditure by making all goods more expensive - this is the "scale effect".[6] Second, carbon taxes reallocate aggregate expenditure towards greener industries by making browner industries relatively more expensive - this is the "composition effect". Third, carbon taxes reallocate industry expenditure towards greener countries by making goods produced in browner countries relatively more expensive - this is the "green sourcing effect". While the scale effect and the composition effect also occur in a closed economy, the green sourcing effect is specific to international trade and thus captures the environmental gains from trade.

Before we discuss why there is no technique effect in this decomposition, it is worth recalling the intuition of a basic 2×2 Ricardian trade model to see how the environmental comparative advantage logic plays out. Imagine thus a simplified version of our model with two countries, Green and Brown, and two industries, Green-Clean and Brown-Clean. Suppose that Green has lower emissions intensities in both Green-Clean and Brown-Clean,

[5] This decomposition is only exact for infinitesimally small changes. In our application, we therefore break any carbon tax change into a series of small changes, updating the expenditure and emissions shares in every iteration.

[6] To be more precise, carbon taxes reduce aggregate economic activity by moving the world economy away from the laissez-faire equilibrium. In a neoclassical trade model like ours, the laissez-faire equilibrium maximizes aggregate output. This would differ in a trade model with climate damages, where the laissez-faire equilibrium would be distorted. However, we will see that the scale effect is negligibly small in our application, making such considerations unlikely to affect our main result.

thus having an environmental absolute advantage. Additionally, suppose that Green's emissions intensity advantage is particularly pronounced in Green-Clean, thereby giving it an environmental comparative advantage in this Green-Clean.

Consider now the effects of imposing a uniform carbon tax. Given that Green has an environmental absolute advantage, the carbon tax makes Green more competitive in Green-Clean and Brown-Clean relative to Brown. Moreover, given that Green has an environmental comparative advantage in Green-Clean, this competitiveness gain is particularly pronounced in Green-Clean. To restore Brown's competitiveness in Brown-Clean and ensure labor market clearing, Green's wage rises relative to Brown's thus neutralizing Green's environmental absolute advantage. The end result is specialization according to environmental comparative advantage: Green in Green-Clean and Brown in Brown-Clean.

Our decomposition (10) does not include a technique effect because we hold emissions intensities constant. This reflects our focus on measuring the static environmental gains from trade and does not imply that dynamic environmental gains from trade are impossible. For example, international trade might accelerate green innovation induced by carbon taxes by allowing firms to leverage their innovations in larger markets. Additionally, in a static model with firm heterogeneity, a technique effect could occur if international trade leads to a reallocation of resources across firms with different emissions intensities. We leave these potentially important extensions for future work.

3 Calibration

3.1 Methodology

To take the model to the data, we use the Dekle et al. (2007) "exact hat algebra", which has become standard in the literature. By expressing the equilibrium conditions in changes relative to the baseline, we eliminate the need to estimate the preference shifters $a_{is'}$ and $b_{is's}$, the productivity shifters A_{js}, and the iceberg trade costs $\tau_{is'j}$. This approach also ensures that the model perfectly matches the global pattern of production and international trade in the baseline scenario.

To solve for a counterfactual equilibrium given a schedule of carbon taxes, we reduce the model to a parsimonious $N \times S$ system and solve it numerically using a nested fixed point routine. To calibrate the model, we need the $N \times N \times S$ matrix of trade flows in final goods, the $N \times N \times S \times S$ matrix of trade flows in intermediate goods, the $N \times S$ vector of greenhouse gas emissions, and estimates of the elasticities $\eta_{s'}$ and $\sigma_{s'}$.[7]

3.2 Data

Data on trade flows for both intermediate and final goods are sourced from the OECD Inter-Country Input-Output (ICIO) tables (OECD, 2023). These tables cover the entire world economy, broken down into 45 industries and 67 countries, including an aggregate Rest of the World, from 1995 to 2018. We calibrate the model using the 2018 data, but we utilize the entire dataset when estimating the key elasticities of the model, as explained below.

Data on greenhouse gas emissions in CO_2 equivalents are constructed by combining three different datasets: the OECD Carbon Dioxide Emissions Embodied in International Trade dataset (TECO2) (OECD, 2021), the FAOSTAT Emissions Totals dataset (FAO, 2023), and the European Commission's Emissions Database for Global Atmospheric Research (EDGAR) (European Commission, 2023). The TECO2 dataset provides CO_2 emissions from fuel combustion across the 45 industries and 67 countries included in the OECD ICIO tables.

To extend emissions coverage and include non-energy-related emissions, we incorporate CO_2, CH_4, and N_2O emissions from the remaining two datasets. Specifically, we use FAOSTAT data for emissions from agriculture, forestry, and land use, and the EDGAR database for emissions from industrial processes, product use, and fugitive emissions. Together, these datasets cover approximately 93% of worldwide greenhouse gas emissions. More details on how we combine these datasets are provided in Appendix A.

[7] Appendix B and C provide a full characterization of the equilibrium in changes and of our solving algorithm.

While our data thus provides a comprehensive coverage of world production, trade, and trade-related emissions, it comes with two notable limitations. First, we can only calculate emissions intensities based on trade values, even though a more realistic approach would involve trade volumes. This limitation arises because the OECD's ICIO tables only provide trade values, and reliable price deflators at this level of aggregation are unavailable. Consequently, in our counterfactual scenarios, changes in emissions reflect not only shifts in trade volumes but also fluctuations in prices.

Second, we cannot differentiate emissions intensities by destination. For example, we are limited to assuming that a ton of German steel has the same emissions intensity in Germany as it has in the US. Notice that this is actually consistent with the iceberg formulation of transport emissions implicit in our model. One ton of German steel has higher embodied emissions in the US than in Germany since, say, 20% "melts away" in transit. However, this also makes German steel 20% more expensive in the US so that the emissions intensity is the same.

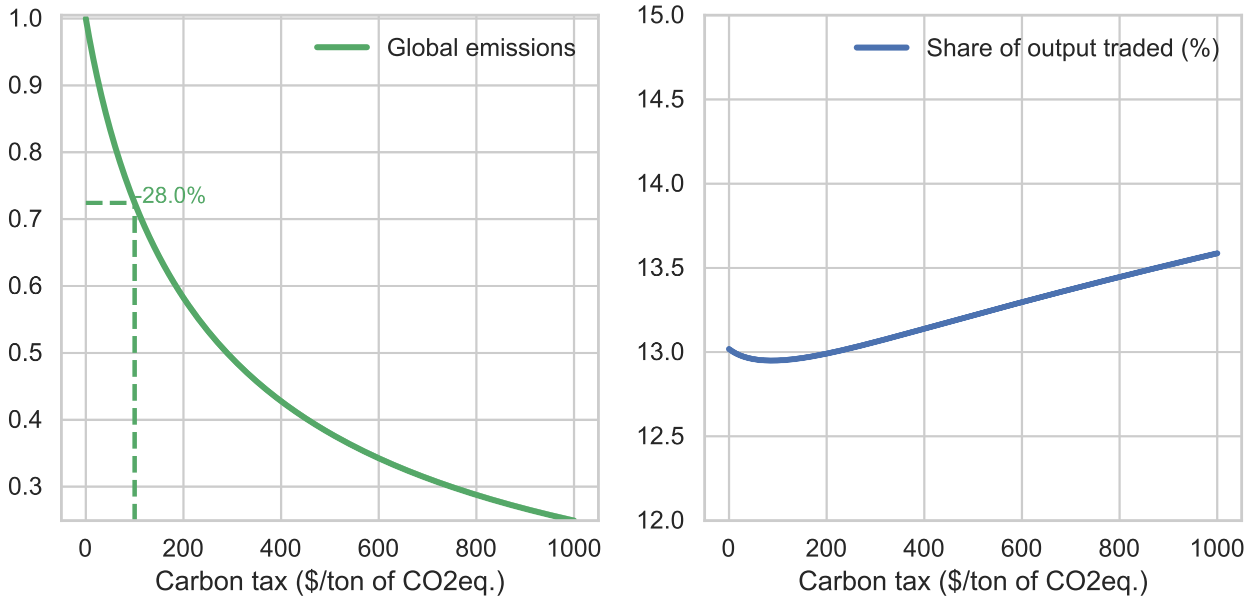
3.3 Estimation

Table 1: Elasticities Summary Statistics

N	Mean	SD	Min	Max
42	3.61	0.86	1.78	5.86

We estimate the elasticities of substitution using the standard methodology of Caliendo and Parro (2015), assuming for simplicity that $\sigma_{s'} = \eta_{s's} = \eta_{s'}$. This approach involves using a fixed-effects model to identify the elasticities from the impact of import tariffs on trade flows, utilizing all available years in our dataset. Elasticities that are negatively signed, statistically insignificant, or unestimable due to insufficient tariff data (notably in the service sectors) are replaced with the mean value. Table 1 provides the summary statistics, showing

Figure 1: Aggregate effects of carbon taxes



Note: The left panel shows the proportional reduction in global greenhouse gas emissions for varying levels of carbon taxes. The right panel shows world trade as a share of gross production.

that our estimates fall within the usual range.[8]

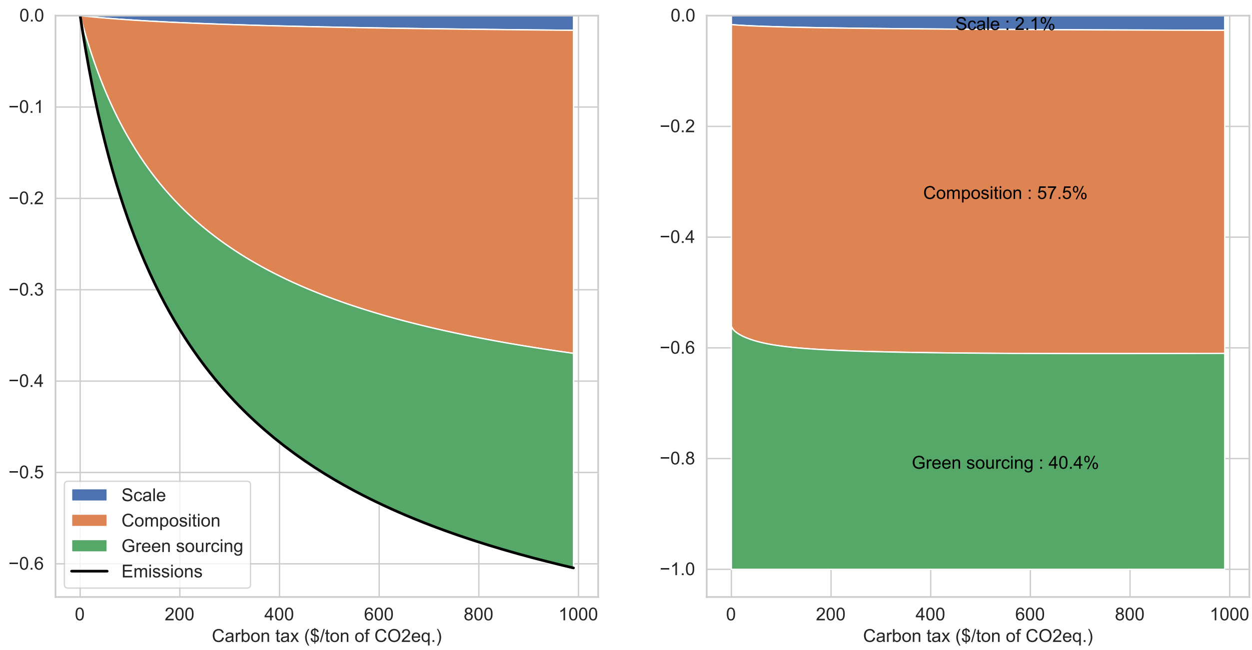
4 Results

4.1 Aggregate effects of carbon taxes

Figure 1 summarizes the aggregate effects of carbon taxes, relative to a no-carbon-tax benchmark in 2018. The left panel shows the proportional reduction in global greenhouse gas emissions for varying levels of carbon taxes. As one would expect, greenhouse gas emissions are strongly decreasing in the carbon tax, with the global emissions reduction reaching 28% for our benchmark carbon tax of $\$100/tCO_2e$. The right panel depicts world trade as a share of gross production for varying levels of carbon taxes. Strikingly, the trade share does not change much with carbon taxes, suggesting that trade is part of a sustainable economy no matter how ambitious climate policies become.

[8] We have also experimented using the alternative methodology of Fontagné et al. (2022) and found that our main results remain unchanged.

Figure 2: Decomposition of emissions reductions



Note: The left panel shows the proportional reduction in greenhouse gas emissions for varying levels of carbon taxes decomposed into three effects. The right panel shows the contributions of each effect to the overall emissions reduction for varying levels of carbon taxes.

4.2 Environmental gains from trade

Figure 2 decomposes the aggregate effects of carbon taxes into a scale effect, a composition effect, and a green sourcing effect following decomposition (10). The left panel shows the proportional reduction in greenhouse gas emissions for varying levels of carbon taxes decomposed into these three effects. The right panel shows the contributions of each effect to the overall emissions reduction for varying levels of carbon taxes. Recall that the green sourcing effect captures the environmental gains from trade brought about by specialization according to environmental comparative advantage.

The green sourcing effect accounts for more than one-third of the emissions reductions brought about by the carbon tax. This is the main result of the paper, suggesting that climate policies can unlock substantial environmental gains from trade. Specifically, the scale effect accounts for 2.1%, the composition effect for 57.5%, and the green sourcing effect for 40.4% of the overall emissions reduction on average. These shares remain relatively stable across the considered range of carbon tax rates.

4.3 Environmental comparative advantage

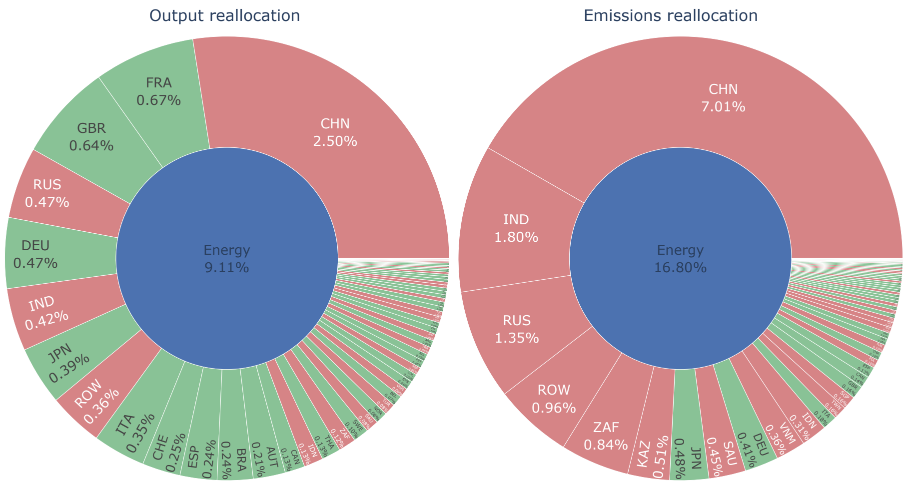
Figure 3 illustrates how the carbon tax reduces emissions by reallocating production across countries in two selected sectors. The left circles indicate where output grows (in green) and falls (in red), with the number in the blue circle representing the share of output being reallocated. The right circles display the associated emissions reductions (in red) and emissions increases (in green), with the number in the blue circle showing the overall emissions reduction. To be clear, the output growth rates in the left circles are expressed in percentages of baseline world output in the sector and sum to zero. The emissions growth rates in the right circles are expressed in percentages of baseline world emissions in the sector and sum to the negative number shown in blue.

The top two circles show the adjustment in the energy sector, highlighting that a cross-country reallocation of 9.1% of sectoral output results in a 16.8% reduction in sectoral emissions. The bottom two circles illustrate the adjustment in the agricultural sector, demonstrating that a cross-country reallocation of 8.0% of sectoral output results in a 23.3% reduction in sectoral emissions. This works because the output elasticity of emissions is systematically larger in countries that lose market shares. For example, China's loss of 2.5% of world energy output leads to a 7.0% reduction in world energy emissions so that the elasticity is $7.0/2.5 = 2.8$. Conversely, France gains 0.67% of world energy output, leading to a 0.08% increase in emissions, with an elasticity of $0.08/0.67 = 0.1$. This is the essence of specialization according to environmental comparative advantage.

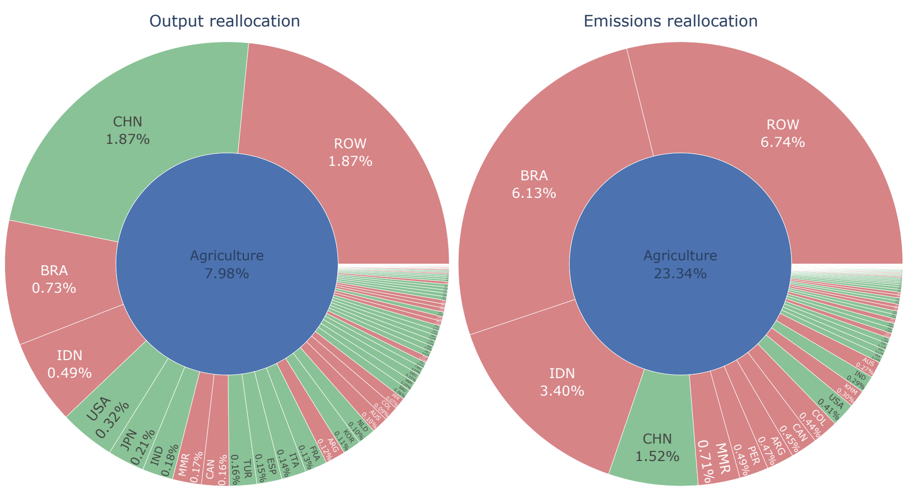
4.4 Incomplete tax coverage

Figure 4 illustrates the emissions reductions resulting from a \$100/tCO_2e carbon tax rate applied only in a subset of industries or countries. The left panel examines carbon taxation schemes applying to all countries but only some industries, starting with the energy sector

Figure 3: Environmental comparative advantage in selected sectors



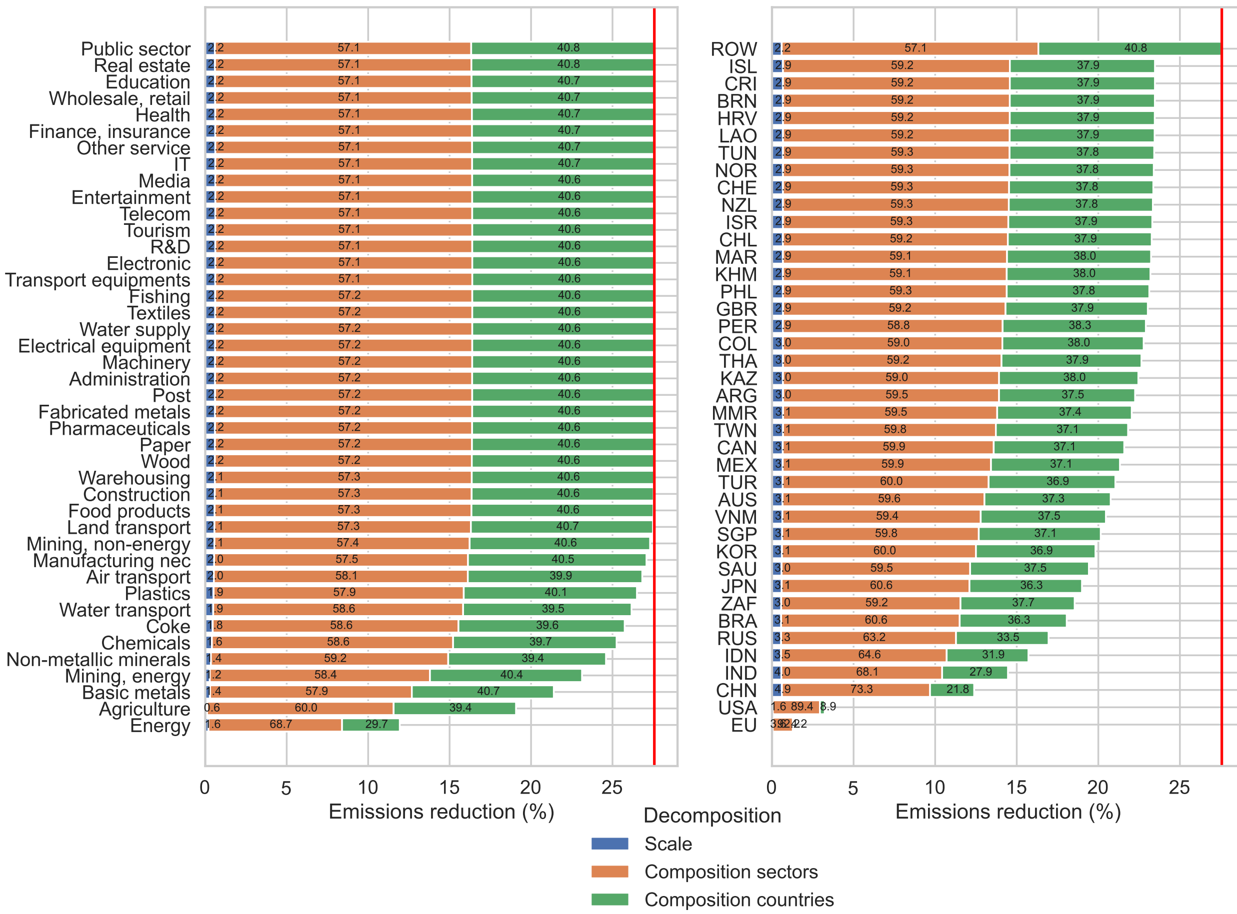
(a) Energy sector



(b) Agricultural sector

Note: This figure illustrates how the carbon tax reduces emissions by reallocating production across countries in two selected sectors. The left circles indicate where output grows (in green) and falls (in red), with the number in the blue circle representing the share of output being reallocated. The right circles display the associated emissions reductions (in red) and emissions increases (in green), with the number in the blue circle showing the overall emissions reduction.

Figure 4: Incomplete tax coverage



Note: This figure illustrates the emissions reductions resulting from a \$100/tCO$_2$e carbon tax rate applied only in a subset of industries (left) or countries (right). Industries and countries are added cumulatively from bottom to top.

only and then adding other industries cumulatively. The right panel explores carbon taxation schemes applying to all industries but only some countries, starting with the EU and then adding other countries cumulatively.

International trade remains a strong force multiplier for carbon taxes even with incomplete carbon tax coverage. Since the environmental gains from trade are brought about by a reallocation of market shares from relatively brown countries to relatively green countries, it is not surprising that a critical mass of countries is needed for the green sourcing effect to account for a meaningful share of the overall emissions reductions. In contrast, a critical mass of industries is not necessary for trade to play an important role.

5 Conclusion

In this paper, we demonstrate that climate policy can unlock substantial environmental gains from trade by encouraging countries to specialize according to their environmental comparative advantage. We illustrate this point by examining the effects of a carbon tax within a quantitative trade model. Our main finding is that the environmental gains from trade account for over one-third of the total reduction in greenhouse gas emissions brought about by the carbon tax. This result holds across a wide range of carbon tax rates and coverages.

We identify two particularly promising avenues for future research. First, it would be valuable to explore a version of the model with heterogeneous firms. We hypothesize that this would reveal additional static environmental gains from trade, resulting from the reallocation of resources from browner firms to lower-emission greener firms. Second, it would be interesting to allow emissions intensities to respond endogenously to carbon taxes. We conjecture that this would uncover additional dynamic environmental gains from trade, driven by the diffusion of green technology or scale effects that make green innovation more profitable.

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A Data treatment

Aggregations

To avoid sparseness of the input-output table and zero gross outputs, we aggregate the following countries:

- Luxembourg and Belgium: subsequently labeled `BEL` in all data

- Hong-Kong and China: subsequently labeled `CHN`
- Malaysia and Singapore: subsequently labeled `SGP`

as well as the following sectors:

- 'Mining and quarrying, energy producing products' [D05T06] with 'Mining support service activities' [D09]: subsequently labeled as [D05T06] (Mining, energy)
- 'Motor vehicles, trailers and semi-trailers' [D29] with 'Other transport equipment' [D30]: subsequently labeled [D29T30] (Transport equipment)

These aggregations leave us with a sample of 64 countries (incl. ROW aggregate) and 42 sectors from 1995 to 2018.

ICIO

The raw ICIO tables records negative values for some accounts of final consumption or value added. As the model cannot accommodate these negative values, we redistribute the negative parts in the table while respecting the following constraints:

- the sum of the columns and the sum of the rows must remain equal,
- the technical coefficients within the IO table (intermediate input spending over gross output ratio, corresponding to the parameters γ in the model) must remain constant equal to the raw ratios.

FAO

We keep only FAO Tier 1 emissions by subcategories belonging to the category 'Agricultural Land' with the exception of 'On-farm Energy Use', since these emissions are already contained in the TECO2 emission data.[9] The remaining observations are then aggregated into

[9] The category 'Agricultural Land' includes the following subcategories: 'Fires in humid tropical forests', 'Fires in organic soils', 'Net Forest conversion', 'Drained organic soils', 'Synthetic Fertilizers', 'Crop Residues', 'Manure left on Pasture', 'Manure applied to Soils', 'Manure Management', 'Enteric Fermentation', 'Savanna fires', 'Burning - Crop residues', 'Rice Cultivation', 'On-farm Energy Use'

the 64 countries with the ROW aggregate and are assigned to the 'Agriculture' sector.

EDGAR

We first combine different time series extracts of the EDGAR database, namely the 'CH4', 'CO2_excl_short-cycle_org_C' and 'N2O' data sheet by converting the emissions into CO_2 equivalents according to the respective AR4 100-year GWP value.[10] We then aggregate the data into our 63 sample countries and create the ROW aggregate with the remaining countries. To assign the IPCC emission categories to our various sample sectors, we rely on the exact definition of the IPCC emission category compared to the ISIC rev.4 codes comprised in our sample sector definition.

For IPPC category 'industrial process and product use emissions' (chapter 2), we apply the following conversion:

IPCC category	Name	Sample sector
2.A	Mineral Industry	Non-metallic minerals
2.B	Chemical Industry	Chemicals
2.C	Metal Industry	Basic metals
2.E	Electronics Industry	Electronic
2.F	Product Uses As Substitutes For Ozone Depleting Substances	Energy

For the IPCC categories "fugitive emissions" (chapter 1.B) we proceed in two steps. Based on the categories definitions we have a direct mapping for the subcategory 'Oil and Natural Gas' (1.B.2) assigned to the sample sector 'Mining, energy'. The subcategory 'Solid Fuels' (1.B.1) however matches with different sample sectors: 'Mining, energy', 'Mining, non-energy', 'Wood', and 'Coke, petroleum'. We therefore disaggregate the IPCC aggregate "Solid fuelds" into the respective sample sectors by using as a disaggregation weights the share of emissions from fuel burning of each sample sector in the total.[11]

[10]The AR4 100-year GWP values are 25 for CH_4 and 298 for N_2O.

[11]Note that we did not include the IPCC categories 2.D 'Non-Energy Products From Fuels and Solvent Use' and 2.G 'Other Product Manufacture and Use' since a clean mapping from the IPCC categories to the corresponding sample sectors is not as easily separable.

B Model - Equilibrium in Changes

This section describes the model equilibrium in changes using Dekle et al. (2007)'s "exact hat algebra". This involves re-writing variables as linear changes from the baseline. In what follows, a baseline version of a variable x is denoted by x^B. The proportional change is then given by $\tilde{x} = x/x^B$.

Following this procedure, changes in the demand for final goods, the demand for inputs, price indexes, and ex-factory prices are given by:

$$\widetilde{q}_{is'j} = \widetilde{I}_{s'j}[\widetilde{p}_{is'}(1+t^e_{is'j})]^{-\sigma_{s'}} \; \widetilde{P}^{c\;(\sigma_{s'}-1)}_{s'j} \tag{11}$$

$$\widetilde{P}^{c}_{s'j} = \left(\sum_i [\widetilde{p}_{is'}(1+t^e_{is'j})]^{(1-\sigma_{s'})}\left(\frac{q^B_{is'j}p^B_{is'j}}{I^B_{s'j}}\right)\right)^{\frac{1}{(1-\sigma_{s'})}} \tag{12}$$

$$\widetilde{m}_{is'js} = \widetilde{E}_{s'js}[\widetilde{p}_{is'}(1+t^e_{is'j})]^{-\eta_{s's}} \; \widetilde{P}_{s'js}^{(\eta_{s's}-1)} \tag{13}$$

$$\widetilde{P}_{s'js} = \left(\sum_i [\widetilde{p}_{is'j}(1+t^e_{is'j})]^{(1-\eta_{s's})}\left(\frac{m^B_{is'j}p^B_{is'js}}{E^B_{s'js}}\right)\right)^{\frac{1}{(1-\eta_{s's})}} \tag{14}$$

$$\widetilde{p}_{js} = \widetilde{w}_j^{\gamma_{j,Ls}} \prod_{s'} \widetilde{P}_{s'js}^{\gamma_{s'js}} \tag{15}$$

Changes in the market clearing conditions are given by:

$$\widetilde{I}_{s'j} = \sum_s \widetilde{w}_j \widetilde{L}_{js}(w^B_j L^B_{js}) + \sum_{i,s',s} \widetilde{p}_{is'}\widetilde{m}_{ijs's}t^e_{ijs'}(p^B_{is'j}m^B_{is'js}) + D^B_j \tag{16}$$

$$\widetilde{E}_{js} = \sum_i \left(\widetilde{p}_{js}\widetilde{q}_{jsi}(p^B_{jsi}q^B_{jsi}) + \sum_{s'} \widetilde{p}_{js}\widetilde{m}_{jsis'}(p^B_{jsi}m^B_{jsis'})\right) \tag{17}$$

$$\sum_s \frac{\widetilde{E}_{js}}{\widetilde{w}_j} L^B_{js} = L_j \tag{18}$$

C Solving algorithm

In this section, we detail how we reduce the model in changes presented above to a $N \times S$ system that we use to back out counterfactual results.

Equations (11) and (12) imply that :

$$\widetilde{q}_{is'j} = \widetilde{I}_j \widetilde{q}_{is'j}{}^{\circ} \tag{19}$$

where $\widetilde{q}_{is'j}{}^{\circ} = [\widetilde{p}_{is'}(1 + t^e_{is'j})]^{-\sigma_{s'}} \; \widetilde{P}^{c}_{s'j}{}^{(\sigma_{s'}-1)}$ only depends on the change of prices and the baseline. It is useful to note that this inverse is linear in any change of set of prices : $\widetilde{q}_{is'j}{}^{\circ}(\alpha\widetilde{p}) = \widetilde{q}_{is'j}{}^{\circ}(\widetilde{p})/\alpha$. This is the most general expression of the change of quantities traded so that the condition of consumer spending is respected by construction because : $\sum_{i,s'} \widetilde{p}_{is'}(1 + t^e_{is'j})\widetilde{q}_{is'j}{}^{\circ}(p^B_{is'j} q^B_{is'j}) = I^B_j$. The form of this expression represents that if the income of the consumer increases (or decreases), he will proportionally increase his consumption from every country/sector. $\widetilde{q}_{is'j}{}^{\circ}$ contains all the information of the reorganisation of his consumption if his income didn't change in the counterfactual world.

Similarly, for intermediates, equation (13) together with $\widetilde{E}_{s'js} = \widetilde{E}_{js}$ imply that :

$$\widetilde{m}_{is'js} = \widetilde{E}_{js} \widetilde{m}_{is'js}{}^{\circ} \tag{20}$$

where $\widetilde{m}_{is'js}{}^{\circ} = [\widetilde{p}_{is'}(1 + t^e_{is'j})]^{-\eta_{s's}} \; \widetilde{P}_{s'js}{}^{(\eta_{s's}-1)}$ has the same properties as $\widetilde{q}_{is'j}{}^{\circ}$. The construction makes sure that the producer spending is respected.

Having the consumer and producer spending respected by construction, we need to compute the consumer and producer revenue. We use equations (18) with $\widetilde{E}_{js} = \widetilde{Y}_{js}$ to compute the wages change under a change of spending of the producer:

$$\widetilde{w}_j = \frac{\sum_s \widetilde{E}_{js} L^B_{js}}{L_j} \tag{21}$$

We have then made sure that the solution respects the labor market clearing condition and the constitutive equation of production $L_{js} = \gamma_{j,Ls} \frac{Y_{js}}{w_j}$, and we can write the consumer revenue and producer spending from the consumer and producer clearing equations :

$$\widetilde{I}_j I^B_j = \sum_s \widetilde{E}_{js} L^B_{js} w^B_j + \sum_{i,s'} \widetilde{I}_j \widetilde{p}_{is'} t^e_{is'j} \widetilde{q}_{is'j} \circ (p^B_{is'j} q^B_{is'j}) + \sum_{i,s',s} \widetilde{E}_{js} \widetilde{p}_{is'} t^e_{is'j} \widetilde{m}_{is'js} \circ (p^B_{is'j} m^B_{is'js}) + D^B_j \tag{22}$$

$$\widetilde{E}_{is'} E^B_{is'} = \sum_j \widetilde{I}_j \widetilde{p}_{is'} \widetilde{q}_{is'j} \circ (p^B_{is'j} q^B_{is'j}) + \sum_{j,s} \widetilde{E}_{js} \widetilde{p}_{is'} \widetilde{m}_{is'js} \circ (p^B_{is'j} m^B_{is'js}) \tag{23}$$

We then use (22) in (23):

$$\begin{aligned} \widetilde{E}_{is'} E^B_{is'} = \widetilde{p}_{is'} \Bigg(& \sum_{j,s} \widetilde{E}_{js} \left[\widetilde{q}_{is'j} \circ (p^B_{is'j} q^B_{is'j}) \frac{L^B_{js} w^B_j + \sum_{i,s'} \widetilde{m}_{is'js} \circ \widetilde{p}_{is'} t^e_{is'j} (p^B_{is'j} q^B_{is'j})}{I^B_j - \sum_{i,s'} \widetilde{q}_{is'j} \circ \widetilde{p}_{is'} t^e_{is'j} (p^B_{is'j} q^B_{is'j})} + \widetilde{m}_{is'js} \circ (p^B_{is'j} m^B_{is'js}) \right] \\ & + \sum_j \frac{D_j \widetilde{q}_{is'j} \circ (p^B_{is'j} q^B_{is'j})}{I^B_j - \sum_{i,s'} \widetilde{p}_{is'} t^e_{is'j} \widetilde{q}_{is'j} \circ (p^B_{is'j} q^B_{is'j})} \Bigg) \end{aligned} \tag{24}$$

$$\widetilde{p}_{js} = \left(\sum_{s'} \widetilde{E}_{js'} \frac{L^B_{js'}}{L_j} \right)^{\gamma_{j,Ls}} \prod_{s'} \widetilde{P}_{s'js}^{\ \gamma_{s'js}} \tag{25}$$

with the last equation expressing the cost of production from the solution of the cost minimization of the production costs of the producer (15). We have thus reduced the equations to a system of two non-linear equations (24) and (25) of the two fundamental hat quantities $(\widetilde{E}, \widetilde{p})$. Since we have explicit expressions of the variables on the right hand side, we can solve numerically this system with a nested fixed point routine.

The solution space of this system of equations is of dimension 1, any linear transformation

$\alpha(\widetilde{E}_{\text{sol}}, \widetilde{p}_{\text{sol}})$ of a solution of the system is also solution. We need to add one numeraire constraint to make the solution unique. Our benchmark results use the global average wage as the numeraire.