Trump, Trade, and Emissions*

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Abstract

This paper examines the unintended effects of noncooperative tariff hikes on global greenhouse gas emissions. Using a multi-country, multi-industry quantitative trade policy model, we evaluate protectionist and retaliatory scenarios shaped by the current geopolitical landscape and assess their impact on the carbon footprint of international trade. Our findings reveal that while noncooperative tariffs suppress economic activity - leading to modest emission reductions - they also restructure trade networks in ways that increase reliance on carbon-intensive production. As a result, arbitrary protectionist measures risk driving globalization towards a less sustainable path.

*This work was developed after a study on the effects of Trump's trade policy on the Norwegian economy. All errors remain our own.

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1 Introduction

The outcome of the 2024 U.S. presidential election has reignited debates over global trade policy, heightening the likelihood of stricter noncooperative measures in the near term. As in the 2018 trade war initiated by the U.S., this includes potential discretionary tariff hikes, as well as retaliatory responses. However, this time, the political discourse signals a trade conflict of greater scale and intensity, one that could target more countries, more sectors, and impose even steeper trade barriers across the global economy.

While primarily designed to advance economic interests, protectionist measures also have significant environmental implications, particularly for the carbon footprint of production and trade (Copeland and Taylor, 2022). A key debate is whether they mitigate or exacerbate climate change. Some political and economic leaders argue that protectionism could benefit the environment, especially when adopted by a relatively green economy. For example, in the 2024 U.S. vice presidential debate, Vice President J.D. Vance claimed that reshoring American production and reducing overseas manufacturing would help combat climate change, asserting that "the U.S. is the cleanest economy."[1]

In this paper, we challenge this notion by examining the unintended environmental consequences of protectionism through a modern quantitative framework. Our analysis builds on Le Moigne, Lepot, Ossa, Ritel and Simon (2024), which demonstrates that global climate policies leverage international trade to achieve greater reductions in greenhouse gas emissions by encouraging countries to specialize according to their environmental comparative advantage. In contrast, we show that protectionist measures, in the form of noncooperative tariffs, have the *opposite* effect, restructuring trade networks in ways that increase global reliance on carbon-intensive production. Surprisingly, this occurs when such policies are implemented by a relatively green economy like the U.S.

To quantitatively assess these effects, we employ a multi-country, multi-industry trade

[1] Vice President J.D. Vance made this argument during the 2024 U.S. Vice Presidential Debate, hosted by CBS News. The full transcript is available at: https://www.cbsnews.com/news/full-vp-debate-transcript-walz-vance-2024/.

policy model with input-output linkages (Caliendo and Parro, 2015), calibrated to 64 regions and 45 industries worldwide. This framework captures the complexity of global production networks, where greenhouse gas (GHG) emissions arise at every stage of production. To isolate the impact of tariff hikes on emissions through changes in trade networks, we employ a decomposition inspired by the scale-composition-technique approach widely used in environmental economics (Grossman and Krueger, 1991). Tariffs reduce emissions through three channels: (1) the scale effect, by lowering aggregate expenditure; (2) the composition effect, by shifting expenditure across industries; and (3) the sourcing effect, by reallocating production across countries. By quantifying this third effect—henceforth the green sourcing effect—we capture how tariff-induced shifts in global production patterns and sourcing decisions alter the carbon footprint of international trade.

Our choice of counterfactual scenarios is guided by the stated trade policy preferences of the current U.S. administration, along with insights from the noncooperative tariffs enacted during the 2018 trade war, as documented by Fajgelbaum et al. (2020). As of 2025, President Donald Trump has repeatedly proposed changes to the U.S. tariff schedule, using the threat of tariff hikes as a bargaining tool to achieve various economic objectives. We focus on a major policy shift that he emphasized throughout his campaign and after his election: imposing tariffs on all U.S. imports, with particularly steep rates targeting Chinese goods. Among the numerous trade measures dominating the 2025 news cycle, we consider this scenario a baseline for evaluating the environmental consequences of widespread protectionism that resonates with the current geopolitical dynamics.

When determining cross-sector variation in this counterfactual tariff schedule, we draw from patterns observed in the 2018 trade war. As Fajgelbaum et al. (2020) document, tariff adjustments during this period were largely uniform across sectors, with nearly all affected products facing either 10% or 25% tariff increases. Notably, this pattern diverges from conventional economic explanations for tariff setting. A long-standing literature, beginning with Johnson (1953), suggests that countries impose import tariffs to improve their terms of trade, with tariff levels determined by the export supply elasticity of each sector. However, Fajgelbaum et al. (2020) find no meaningful correlation between average 2018 sector-level tariff rates and the foreign export supply elasticities estimated by Broda et al. (2008), casting doubt on the idea that these tariffs were set based on standard economic considerations. Additionally, the lack of sectoral variation suggests that lobbying played a minimal role in shaping these policies.

Given this context, we depart from the standard approach in the quantitative trade war literature (Ossa, 2014; Lashkaripour, 2021) and model our counterfactual scenarios as exogenous, uniform tariff changes informed by observed policy preferences rather than the strategic interactions of welfare-maximizing governments. Accordingly, we consider both unilateral uniform tariffs, where the United States imposes tariffs in all sectors without retaliation, and scenarios where key trade partners respond symmetrically.[2,3]

Results show that tariff-induced price changes shift trade away from the U.S. and its main trade partners—where production is relatively greener—toward more carbon-intensive producers abroad. To examine this effect in detail, we first explain the economic rationale behind our counterfactual tariff and retaliation scenarios before linking them to their environmental consequences.

Import tariffs are a beggar-thy-neighbor policy, benefiting the protectionist country at the expense of its trade partners. In response, affected countries have a strong incentive to retaliate to counteract economic losses. While tariffs initially boost domestic production and suppress foreign output, this effect is constrained by supply chain dependencies, as many

[2] Specifically, the scenarios include a 10% tariff on all countries (US10); 10% or 20% on all countries and 60% on China (US1060 and US2060); 10% on all countries, 60% on China, and 0% on the EU (US1060EU0); and 10% on a selected set of sectors (US10Sectors). Each scenario has a corresponding retaliation case, where trade partners impose equivalent tariffs against the U.S., indicated by "Retal" in the scenario name. Other tariffs remain unchanged.

[3] Our counterfactual scenarios include tariffs on both goods and services sectors. While trade policy analysis typically focuses on goods trade, there is no reason to assume that services sectors will be exempt from U.S. trade actions or retaliation strategies by its partners. For example, reports suggest that the U.S. may leverage trade negotiations to challenge the U.K.'s Digital Services Tax (see: https://www.politico.eu/article/donald-trump-war-tech-taxes-big-problem-britain-keir-starmer/).

domestic industries rely on imported inputs.[4] Additionally, some third countries benefit from trade diversion, either by being exempt from the policy or capturing market share from targeted nations. However, retaliatory tariffs erode any initial gains from protectionism, driving up costs and further distorting trade flows. As a result, the new equilibrium features a weakened global economy, with protectionist countries ultimately losing competitiveness in foreign markets due to tariff-induced price distortions.

This contraction in global economic activity, driven by rising prices, leads to a modest reduction in global emissions, ranging from 0.2% to 0.9%. At first glance, this might appear to be a positive environmental outcome of trade restrictions. However, a decomposition of this effect into scale, composition, and green sourcing effects challenges this interpretation. In fact, the primary driver of emissions reduction is the scale effect, merely reflecting an impoverished global economy. Moreover, we find negative green sourcing effects, meaning that global trade increasingly depends on carbon-intensive sectors—such as basic metals and energy—sourced from high-emission producers like India and China. This result holds across all scenarios and remains robust to variations in tariff levels under unilateral U.S. taxation.[5]

By increasing domestic prices and undermining the competitiveness of its own relatively green economy, U.S. trade wars reverse the environmental benefits of trade. Instead of promoting cleaner production, they redirect trade toward carbon-intensive sectors, increasing reliance on high-emission producers like China and India. Although the quantitative impact on emissions from such trade policies is modest, these policies restructure global trade patterns and push globalization toward a less sustainable trajectory, suggesting even greater long-term environmental damage due to the persistent effects of trade policy (Cox, 2021). Notably, this stands in stark contrast to the environmental gains from trade documented in Le Moigne, Lepot, Ossa, Ritel and Simon (2024), where carbon policies reduce emissions by leveraging open markets and environmental comparative advantage.

[4]See Blanchard et al. (2016) for a theoretical and empirical account of how supply chain linkages alter the costs and benefits of trade protection.

[5]We also find that composition effects are small but do contribute slightly to emissions reductions.

This paper contributes to several strands of the literature. Closely related to our analysis is Shapiro (2021), who documents a systematic environmental bias in trade policy, where tariffs tend to be lower on polluting industries, effectively subsidizing carbon-intensive production. His findings suggest that existing trade policies, rather than being environmentally neutral, implicitly favor emissions-heavy sectors. Our analysis differs in its objective. While Shapiro, in a quantitative exercise, emphasizes the implicit environmental distortions in current tariff schedules, we show that active shifts toward protectionism—such as broad-based tariff hikes—can further exacerbate global carbon dependency by redirecting trade flows away from relatively greener economies.[6]

The recent shift toward protectionism has led to a growing body of research examining the effects of trade policy on the U.S. economy and politics. Autor et al. (2020) show that trade-exposed counties have shifted their voting behavior toward extreme parties, with the 2018 trade war reinforcing Republican support despite its negative impact on employment. Additionally, evidence suggests that U.S. tariffs did not lower prices of targeted imports, leading to a full pass-through into consumer prices (Flaaen et al., 2020; Houde and Wang, 2023; Amiti et al., 2020). As a result, the trade war imposed significant costs on U.S. firms and consumers, with welfare losses estimated at around 3% of GDP (Amiti et al., 2019). Looking ahead, Clausing and Lovely (2024) estimate that Trump's 2024 tariff proposals could further raise consumer costs by 1.8% of GDP, a magnitude similar to our findings on U.S. welfare losses.

Fewer studies examine the effects of a U.S. trade war on other countries. Berthou et al. (2018) estimate that a global 10 percentage point tariff increase could reduce global GDP by up to 3% after two years, with third countries experiencing currency depreciations and weaker stock market performance (Carlomagno and Albagli, 2022). However, some countries may benefit from trade diversion, as seen in the EU during the U.S.-China trade war (Bolt and Mavromatis, 2019). A broader trade war could trigger inflationary pressures, prompting

[6] Due to the level of aggregation in our data, we do not detect an environmental bias in trade policy. Thus, unlike in Shapiro (2021), this factor does not influence our findings.

central banks to raise interest rates, which would dampen investment and consumption (Berthou et al., 2018). While Obst et al. (2024) suggest that a unilateral U.S. tariff could increase U.S. GDP in the long run, retaliation from China would offset these gains. We contribute to this literature by analyzing the real income effects of Trump's 2024 trade policy proposals for all countries.

2 Choice of scenarios

This section outlines the rationale behind the scenarios analyzed in this report. We examine five scenarios in which the U.S. unilaterally imposes tariffs and, for each, a retaliation scenario where U.S. trading partners reciprocate. This results in ten scenarios, summarized in Table 1.

The first scenario assumes that the U.S. imposes a 10% tariff on all countries and all sectors, based on statements made by Trump during his 2024 campaign (Business, 2024). In the retaliation equivalent, all other countries respond with 10% tariffs on the U.S., while tariffs between other countries remain unchanged. The second scenario extends the first by adding a 60% tariff on China, another policy frequently mentioned in Trump's campaign (CNBC, 2024). In the retaliation case, all countries impose a 10

The third scenario considers a similar setting but exempts the EU from the trade war (tariff set to 0), while all other countries face a 10% tariff, and China remains at 60%. While Trump has not explicitly proposed this, it allows us to examine the effects on third countries outside the EU, such as Norway or the UK. As before, in the retaliation scenario, each country matches the tariffs imposed on them by the U.S.

The fourth scenario mirrors the second but raises the base tariff to 20% for all countries, while China remains at 60% (Today, 2024). In the retaliation case, each country imposes tariffs equal to those they face from the U.S.

While these scenarios are simplified representations based on public declarations, we con-

Table 1: Choice of scenarios

Name	Description
US10	US levies a 10% tariff on all countries and all sectors
US1060	US levies a 10% tariff on all countries and all sectors, and a 60% tariff on China
US1060EU0	as above, and the EU can negotiate an exemption (0% tariff)
US2060	US levies a 20% tariff on all countries and all sectors, and a 60% tariff on China
US10Retal	US levies a 10% tariff, each country retaliates with 10% against US
US1060Retal	as above, just US-China both implement 60% against each other
US1060EU0Retal	as above, but exemption for EU (0 tariff between US and EU)
US2060Retal	US levies a 20% tariff, each country retaliates with 20% against US

sider them benchmark cases that capture key aspects of recent U.S. trade policy proposals. They also provide a general framework broad enough to draw robust conclusions about the economic and environmental effects of widespread protectionism. Additionally, we demonstrate that our main result remains robust even when varying the baseline tariff levels under a uniform U.S. taxation scheme, reinforcing the generalizability of our findings.

3 Model

3.1 Setup

We employ a multi-country, multi-sector quantitative trade policy model with input-output linkages (Armington, 1969; Caliendo and Parro, 2015).

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, as well as ad-valorem import tariffs $t_{is'j}$. Countries are endowed with an inelastic supply of workers L_i who are internationally immobile.

3.2 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

$$q_{is'j} = a_{is'} \frac{\left[p_{is'j}\left(1+t_{is'j}\right)\right]^{-\sigma_{s'}}}{\left(P^c_{s'j}\right)^{1-\sigma_{s'}}} \beta_{s'j} I_j \tag{3}$$

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

where $p_{is'j}$ are delivered prices, $t_{is'j}$ are tariffs, $P^c_{s'j}$ 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.

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

$$m_{is'js} = b_{is's} \frac{\left[p_{is'j}\left(1+t_{is'j}\right)\right]^{-\eta_{s'}}}{\left(P^p_{s'j}\right)^{1-\eta_{s'}}} \gamma_{s'js} E_{js}, \tag{7}$$

where $P^p_{s'j}$ are producer price indices.

We close the model by imposing labor and goods market clearing:

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

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

D_i represents the trade deficit, which is exogenous and held fixed in our counterfactuals. A key consideration for our analysis is that President Donald Trump frequently argues that trade policy should be used to reduce U.S. bilateral trade deficits. However, since the trade deficit in our model is policy-blind, this channel is not explicitly captured in our analysis. As an alternative approach, we compute results allowing deficit changes to be proportional to tariff-induced income changes and verify that this assumption does not affect our main findings. Fully endogenizing the trade deficit would require a dynamic framework, which is beyond the scope of this paper.

Emissions are calculated by multiplying the counterfactual value of trade flows with the emissions intensity per dollar of output of a country sector pair:

$$GHG_{is'} = \sum_{s'} \sum_j p_{is'j} \left(q_{is'j} + \sum_s m_{is'js} \right) * e_{is'}$$
$$e_{is'} = \frac{CO2_{is'}}{Y_{is'}}$$

with $e_{is'}$ denoting the exogenous production emission intensity of production of good s' in country i in terms of tons of CO2 emitted per \$ of output. Notice that $e_{is'}$ captures only the emissions directly caused by the production process but not the emissions caused indirectly by the use of inputs.

3.3 Decomposition

To analyze the impact of trade policy on greenhouse gas (GHG) emissions, we develop a decomposition framework inspired by the scale-composition-technique effect commonly used in environmental economics (Grossman and Helpman, 1995; Copeland and Taylor, 2003; Levinson, 2009; Shapiro and Walker, 2018). Our approach closely follows the methodology of Le Moigne, Lepot, Ossa, Ritel and Simon (2024), who use a similar decomposition to examine the environmental gains from trade driven by efficient climate policies.

We write total emissions as $GHG = \sum_i \sum_j \sum_{s'} q_{is'j} E_{is'}$, where $q_{is'j}$ is the quantity of goods flowing from country i in sector s' to country j and $E_{is'}$ is the emissions intensity per quantity. Totally differentiating this expression holding emissions intensities constant, we decompose the overall change in emissions into a scale, composition, and green sourcing effect:

$$d \ln GHG = \underbrace{d \ln q}_{\text{scale effect}} + \underbrace{\sum_s \frac{E_s}{E} d \ln \frac{q_s}{q}}_{\text{composition effect}} + \underbrace{\sum_i \sum_s \frac{E_{is}}{E} d \ln \frac{q_{is}}{q_s}}_{\text{green sourcing effect}}, \tag{10}$$

where $\frac{E_s}{E}$ is the emissions share of a sector, $\frac{q_s}{q}$ is the trade volume share of sector s, $\frac{E_{is}}{E}$ is the emissions share of a country-sector pair, and $\frac{q_{is}}{q_s}$ is the trade volume share of a country-sector pair in the trade volume of that sector. In order to bring this decomposition to the data, we make the assumption that the shares in trade volumes are similar to the expenditure shares in trade values. [7]

Applied to our model, equation (10) captures three channels through which trade policy affects emissions. First, tariffs reduce aggregate expenditure by making all goods more expensive—this is the scale effect. Second, tariffs reallocate expenditure across industries; since

[7] Alternatively, we could write the decomposition in nominal terms with trade flows, but that would make it dependent on the choice of numeraire.

some industries are greener while others are more carbon-intensive, emissions may increase or decrease—this is the composition effect. Third, tariffs reallocate industry expenditure across countries within the same sector, where production emissions vary across locations—this is the green sourcing effect. While the scale and composition effects also occur in a closed economy, the green sourcing effect is specific to international trade and captures the environmental gains from trade. Our decomposition does not include a technique effect, as we assume emissions intensities remain constant.

4 Calibration

4.1 Methodology

To bring the model to the data, we apply the exact hat algebra method of Dekle et al. (2007), a standard tool in the literature. Reformulating the equilibrium conditions in terms of relative changes from the baseline allows us to bypass the estimation of preference shifters ($a_{is'}$, $b_{is's}$), productivity parameters (A_{js}), and iceberg trade costs ($\tau_{is'j}$). This approach also ensures that the model exactly replicates the observed global distribution of production and trade flows in the baseline scenario.

To compute the counterfactual equilibrium under a given carbon tax schedule, we simplify the model into a compact $N \times S$ system and solve it numerically using a nested fixed-point algorithm. Model calibration requires an $N \times N \times S$ matrix of final goods trade flows, an $N \times N \times S \times S$ matrix of intermediate goods trade flows, an $N \times S$ vector of greenhouse gas emissions, and estimates of the elasticities $\eta_{s'}$ and $\sigma_{s'}$.[8]

4.2 Data

Our analysis relies on trade flow, tariffs and greenhouse gas (GHG) emissions data from multiple sources. Trade data for intermediate and final goods come from the OECD Inter-

[8] Appendices D and E detail the equilibrium conditions in changes and the solution algorithm.

Country Input-Output (ICIO) tables, which cover 45 industries and 67 economies over the period 1995–2018. We obtain import tariff data for the same period from the World Bank (WITS). We use 2018 data for model calibration and the full dataset to estimate key elasticities.

Emissions data, measured in CO_2 equivalents, are compiled from OECD's TECO2 dataset, FAOSTAT, and the European Commission's EDGAR database, covering emissions from fuel combustion, agriculture, land use, industrial processes, and fugitive sources. Combined, these sources account for approximately 93% of global GHG emissions. Further details on data integration and methodological choices are provided in Appendix B.

4.3 Estimation

Following Le Moigne, Lepot, Ossa, Ritel and Simon (2024), we estimate the substitution elasticities with the standard approach of Caliendo and Parro (2015), assuming for simplicity that $\sigma_{s'} = \eta_{s's} = \eta_{s'}$. This method relies on a fixed-effects model to infer elasticities from the response of trade flows to import tariffs, leveraging all available years in our dataset. When an estimated elasticity is negative, statistically insignificant, or cannot be identified due to limited tariff data—particularly in service sectors—we replace it with the mean value. Summary statistics in Appendix C confirm that our estimates fall within the typical range in the literature.[9]

5 Results

5.1 Aggregate effects of trade policy across countries

To set the stage for our discussion on the environmental consequences of tariffs, we first examine their economic impact, as it serves as the primary underlying mechanism. Figure

[9]We also tested the alternative methodology of Fontagné et al. (2022) and found that our main results remain robust.

1 presents the real income changes for each unilateral tariff scenario, where no country is allowed to retaliate. The figure distinguishes between EU countries (left) and all other countries (right). The key takeaway is that the U.S. experiences a real income gain in all scenarios, while most other countries face losses. On a global scale, each scenario results in a net real income loss. Specifically, in the US10 scenario[10], U.S. real income increases by approximately 0.5% (blue bar). This result aligns with standard terms-of-trade gains from trade policy, extensively discussed in the theoretical and quantitative trade policy literature (Johnson, 1953; Ossa, 2014).

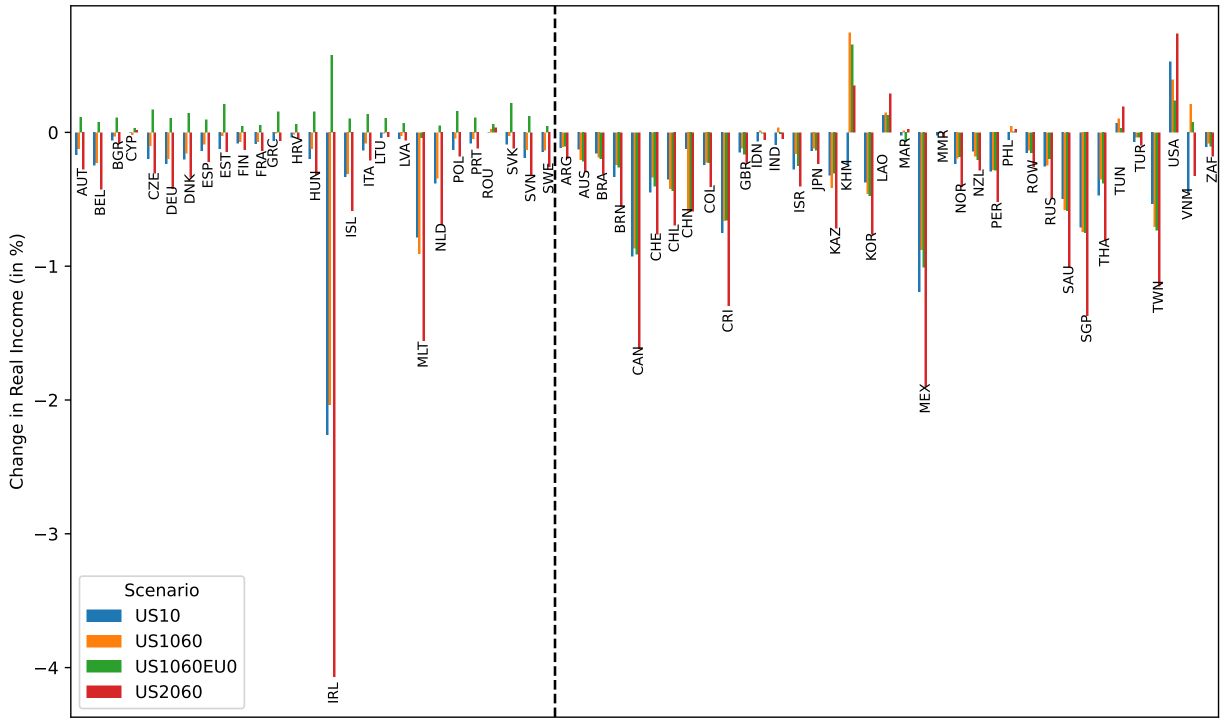
The 20% tariff scenario (red bars) results in the largest gains for the U.S. and the largest losses for most other countries. When the EU is granted an exemption (green bars), each EU country also benefits, experiencing real income gains. In contrast, several of the U.S.'s main trading partners—including Canada, Mexico, Great Britain, and Ireland—face significant real income declines. Interestingly, Cambodia (KHM) benefits from the policy, but only when China is taxed more heavily than other countries, suggesting that Cambodia captures part of China's market share. Meanwhile, Ireland and Malta, often considered tax havens where many U.S. companies operate, experience sharp income losses. Higher tariffs on these countries reduce their exports to the U.S., leading to a steep real income decline—up to 3% for Ireland in the US2060 scenario[11]. The overall decline in real income globally reflects the reduction in economic activity caused by tariff-induced increases in cross-country and cross-sector prices.

Figure 2 presents the same scenarios as Figure 1, but now each country retaliates with an equivalent tariff. For example, if the U.S. imposes a 60% tariff on China, China reciprocates with a 60% tariff on the U.S., while all other trading partners maintain their existing tariff levels. With retaliation, the U.S. now experiences a real income loss in all scenarios, reversing the initial gains seen under unilateral protectionism. Interestingly, EU countries benefit from

[10] US10: The U.S. imposes a 10% tariff on all trading partners, with no retaliation.

[11] US2060: The U.S. imposes a 20% tariff on all trading partners and a 60% tariff on China, with no retaliation.

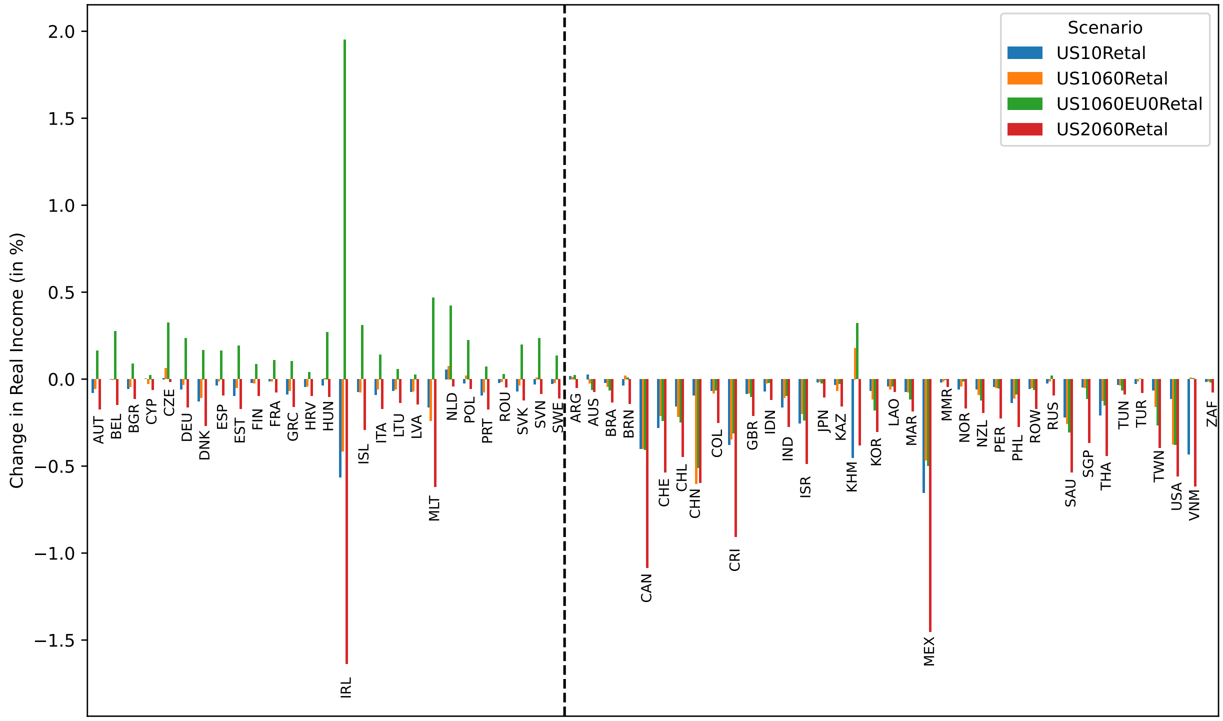
Figure 1: Real Income Changes Unilateral Scenarios



Note: This graph shows the change in real income for each unilateral scenario (e.g. US1060: The US imposes a 10% tariff on all countries and 60% on China, nobody retaliates).

a real income gain when they are exempted from the trade war. Overall, real income losses are smaller for most countries compared to the unilateral case, as retaliation allows trade partners to recover some of the benefits of protectionism. For instance, Ireland initially faced a 3% real income loss in the unilateral US2060 scenario (Figure 1). However, when Ireland retaliates with a 10% tariff on the U.S. in Figure 2, its real income loss drops to 1.5%. Notably, a few countries—including the Czech Republic and the Netherlands—experience a real income gain in all retaliation scenarios, suggesting that certain economies can benefit from the shifting trade dynamics.

Figure 2: Real Income Changes Retaliation Scenarios



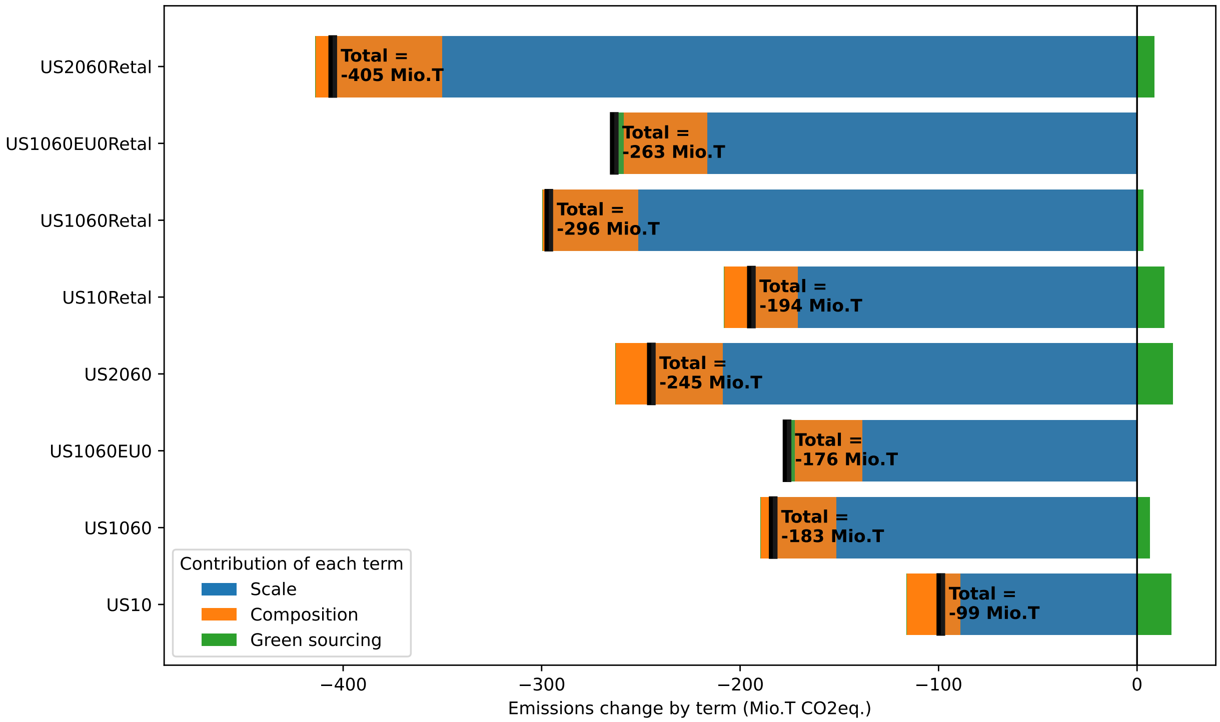
Note: This graph shows the change in real income for each retaliatory scenario (e.g. US1060Retal: The US imposes a 10% tariff on all countries and 60% on China, each country retaliates against the US, but no other tariffs are imposed).

5.2 Effects of trade policy on global emissions

Global emissions decline slightly in each scenario, as shown in Appendix Figure 5. Retaliation scenarios consistently result in larger emission reductions compared to their unilateral counterparts. However, in terms of magnitude, these reductions remain below 1%, making them relatively small compared to policies explicitly designed to curb emissions, such as carbon taxes.

Figure 3 decomposes the decline in emissions into three effects: scale, composition, and green sourcing. From a normative perspective, the scale effect—a reduction in emissions driven by declining economic activity—is the least desirable mechanism for lowering emissions. In contrast, the composition and green sourcing effects are more favorable, as they reallocate economic activity across sectors or countries rather than simply reducing output. For comparison, policies that explicitly target emissions, such as a uniform global carbon

Figure 3: Global emission changes decomposition



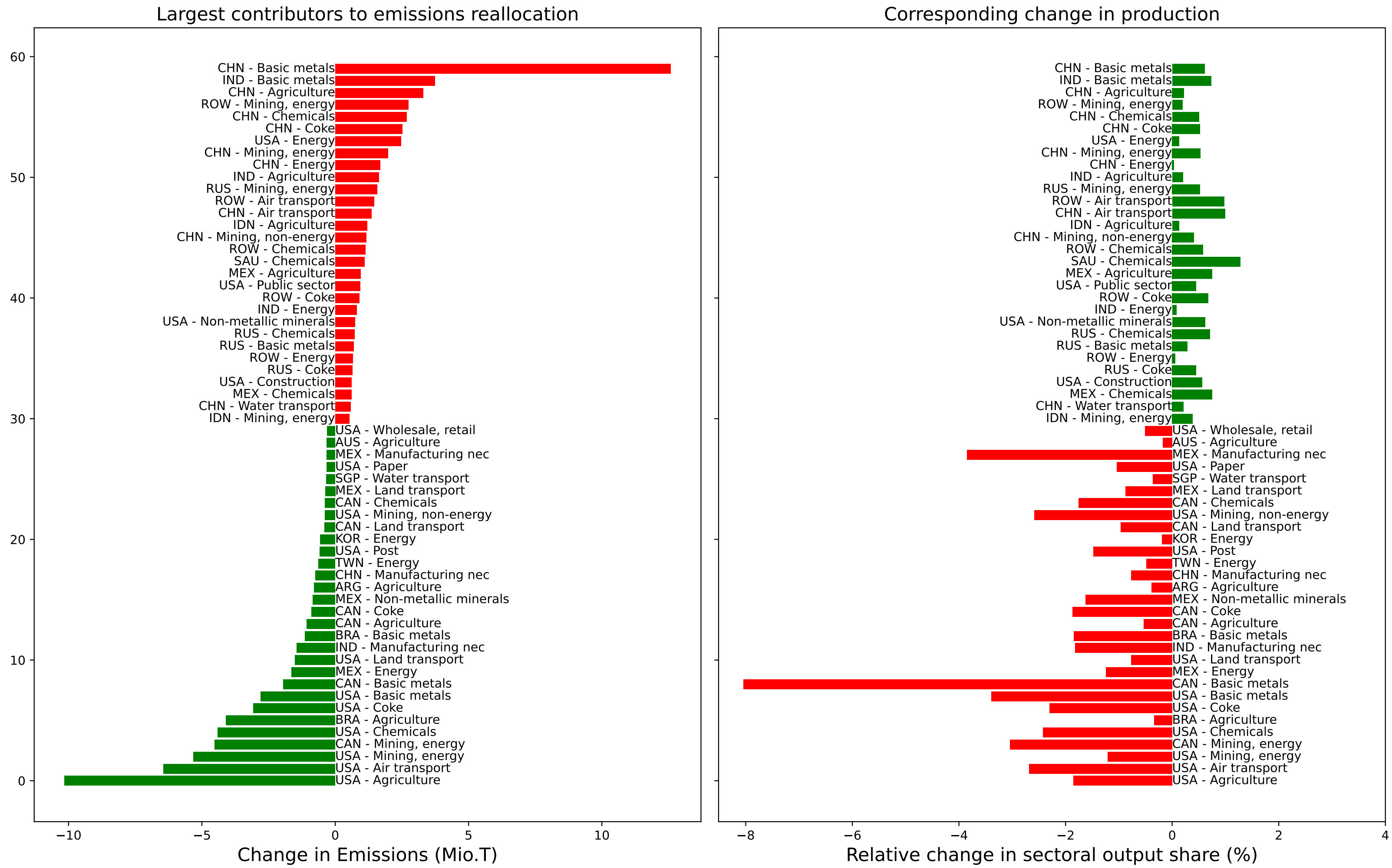
Note: This graph shows the contribution of three effects (scale, composition, green sourcing) to the reduction in greenhouse gas emissions for each policy scenario.

tax (Le Moigne, Lepot, Ossa, Ritel and Simon, 2024) or tariffs without an environmental bias (Shapiro, 2021), minimize scale effects while amplifying composition and green sourcing effects.

Under Trump's trade policy, the scale effect accounts for the largest share of the emissions reduction. Meanwhile, the green sourcing effect is negative, indicating that tariff-induced price changes shift economic activity away from cleaner producers toward more carbon-intensive countries. As a result, Trump's trade policy promotes "brown sourcing" rather than green sourcing. In Appendix Figure 6, we demonstrate that this conclusion remains robust across different levels of uniform U.S. taxation.

Figure 4 illustrates the mechanisms driving the "brown sourcing" effect in the unilateral US10 scenario. The left panel highlights the country-sector pairs contributing the most to emissions changes, where red indicates an increase in emissions and green a decrease. The right panel shows the corresponding changes in production, with green representing increases and red representing decreases. The key takeaway is that the largest emissions increases stem from higher production in carbon-intensive sectors within low- and middle-income countries, particularly China, India, and Russia. Conversely, the largest emissions reductions result from declining production in cleaner economies such as the U.S. and Canada. However, even substantial production declines in cleaner sectors—such as Canadian basic metals—lead to only modest emissions reductions. Overall, these shifts occur because U.S. firms and those in key trade partners lose competitiveness in foreign markets due to the higher costs imposed by protectionist policies. These cost increases arise both directly from tariffs and indirectly through supply-chain linkages. As a result, economic activity shifts toward more carbon-intensive producers, further reinforcing the brown sourcing effect.

Figure 4: Main contributors to brown sourcing



Note: This graph shows the country-sector pairs with the largest change in emissions for the US10 scenario.

6 Conclusion

The renewed prominence of trade policy, particularly following the 2024 U.S. presidential election, underscores its far-reaching economic and environmental implications. This paper demonstrates that while tariffs are primarily enacted for strategic and economic objectives, they inadvertently alter global greenhouse gas emissions. Our findings show that U.S. tariffs lead to a modest decline in global emissions, but this reduction stems not from cleaner production or sourcing, but rather from a contraction in economic activity. More critically, these policies shift production from cleaner economies to more carbon-intensive ones, reversing the environmental gains from trade. Thus, we provide evidence of the unintended climate costs of protectionism, highlighting the need for trade policies that align with, rather than undermine, global climate efforts.

Our analysis opens several avenues for future research. One promising direction is to explore how trade policy influences firms' incentives to adopt cleaner technologies or abate emissions within production. Additionally, incorporating a more detailed representation of transport emissions in quantitative trade models could further refine our understanding of how tariff-induced shifts in trade patterns impact global emissions.

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A Data Sources and Coverage

Our data sources follow the approach of Le Moigne, Lepot, Ossa, Ritel and Simon (2024), integrating trade and emissions data from multiple international databases to ensure broad coverage of global economic activity.

Trade Data: We use the OECD Inter-Country Input-Output (ICIO) tables (OECD, 2023) for trade flow data, which provide a detailed representation of global supply chains. The ICIO tables report both intermediate and final goods trade across 45 industries and 67 economies, including an aggregated Rest of the World category. The dataset spans 1995–2018, with 2018 serving as the baseline year for model calibration, while earlier years are used to estimate key elasticities.

Tariff Data: We obtain bilateral applied import tariffs for 2018 from the World Bank (WITS).

Emissions Data: We compile greenhouse gas (GHG) emissions data, expressed in CO_2 equivalents, from three complementary sources: (i) OECD's TECO2 dataset (OECD, 2021), which reports CO_2 emissions from fuel combustion across the same 45 industries and 67 economies covered in the ICIO tables; (ii) FAOSTAT Emissions Totals dataset (FAO, 2023), which accounts for agriculture, forestry, and land use emissions; (iii) European Commission's EDGAR database (European Commission, 2023), which includes industrial processes, product use, and fugitive emissions.

By integrating these sources, we capture approximately 93% of global GHG emissions, ensuring a comprehensive dataset for analyzing trade-related emissions.

While our data provides extensive coverage of global production, trade, and emissions, it has two key limitations:First, our emissions intensity calculations rely on trade values rather than physical trade volumes. This is due to the ICIO tables reporting trade in monetary terms, with no suitable price deflators available at this level of aggregation. Consequently, in our counterfactual analysis, changes in emissions reflect both shifts in trade volumes and price fluctuations.

Second, we assume that a ton of steel produced in Germany has the same emissions intensity whether it is consumed domestically or exported to the U.S. While this assumption simplifies the analysis, it aligns with the iceberg cost formulation of transport emissions in our model. That is, a ton of German steel delivered to the U.S. effectively carries higher embodied emissions due to transportation losses (e.g., 20% "melting away" in transit). However, because these losses also increase the price of imported goods, the emissions intensity per unit of trade remains unchanged in our framework.

Further details on the data integration process and robustness checks are provided in Appendix B.

B Data treatment

Aggregations

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

- Luxembourg and Belgium: subsequently labeled `BEL` in all data
- Hong-Kong, China 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 economies (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.[12] The remaining observations are then aggregated into the 64 economies 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.[13] We then aggregate the data into our 63 sample economies and create the ROW aggregate with the remaining economies. 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

[12] 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'

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

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.[14]

C Elasticity Estimation

For details on the elasticity estimation, see Le Moigne, Lepot, Ritel and Simon (2024).

Table 2: Elasticities Summary Statistics

N	Mean	SD	Min	Max
42	3.61	0.86	1.78	5.86

[14]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.

D 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:

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

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

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

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

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

Changes in the market clearing conditions are given by:

$$\widetilde{I}_{s'j} = \sum_s \widetilde{w}_j \widetilde{L}_{js}(w^B_j L^B_{js}) + \sum_{i,s',s} \widetilde{p}_{is'}\widetilde{m}_{ijs's}t_{ijs'}(p^B_{is'j}m^B_{is'js}) + D^B_j \tag{16}$$

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

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

E 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 $\widetilde{q}_{is'j}^{\circ} = [\widetilde{p}_{is'} \frac{(1+t_{is'j})}{(1+t^B_{is'j})}]^{-\sigma_{s'}} \ \widetilde{P}^{c\ (\sigma_{s'}-1)}_{s'j}$ 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 : $\sum_{i,s'} \widetilde{p}_{is'}(1+t_{is'j})\widetilde{q}_{is'j}^{\circ}(p^B_{is'j}q^B_{is'j}) = I^B_j$. The form of this expression represents that if the income of the consumer increases (or decreases), she will proportionally increase his consumption from every economy/sector. $\widetilde{q}_{is'j}^{\circ}$ contains all the information of the reorganisation of his consumption if his income did not 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 $\widetilde{m}_{is'js}^{\circ} = [\widetilde{p}_{is'} \frac{(1+t_{is'j})}{(1+t^B_{is'j})}]^{-\eta_{s's}} \ \widetilde{P}_{s'js}^{(\eta_{s's}-1)}$ 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:

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

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 :

$$\widetilde{I}_j I_j^B = \sum_s \widetilde{E}_{js} L_{js}^B w_j^B + \sum_{i,s'} \widetilde{I}_j \widetilde{p}_{is'} t_{is'j} \widetilde{q}_{is'j}{}^{\circ}(p_{is'j}^B q_{is'j}^B) + \sum_{i,s',s} \widetilde{E}_{js} \widetilde{p}_{is'} t_{is'j} \widetilde{m}_{is'js}{}^{\circ}(p_{is'j}^B m_{is'js}^B) + D_j^B \tag{22}$$

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

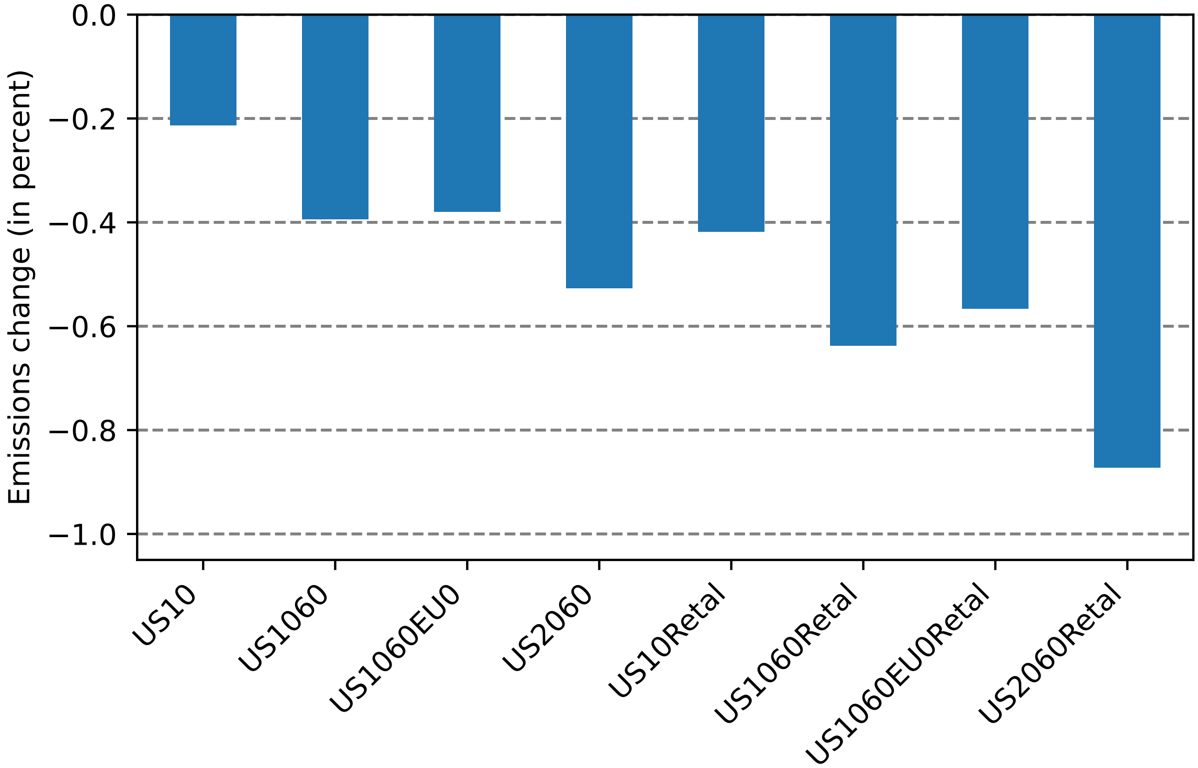
We then use (22) in (23):

$$\begin{aligned}\widetilde{E}_{is'} E_{is'}^B = \widetilde{p}_{is'} \Bigg(& \sum_{j,s} \widetilde{E}_{js} \left[\widetilde{q}_{is'j}{}^{\circ}(p_{is'j}^B q_{is'j}^B) \frac{L_{js}^B w_j^B + \sum_{i,s'} \widetilde{m}_{is'js}{}^{\circ} \widetilde{p}_{is'} t_{is'j} (p_{is'j}^B q_{is'j}^B)}{I_j^B - \sum_{i,s'} \widetilde{q}_{is'j}{}^{\circ} \widetilde{p}_{is'} t_{is'j} (p_{is'j}^B q_{is'j}^B)} + \widetilde{m}_{is'js}{}^{\circ}(p_{is'j}^B m_{is'js}^B) \right] \\ & + \sum_j \frac{D_j \widetilde{q}_{is'j}{}^{\circ}(p_{is'j}^B q_{is'j}^B)}{I_j^B - \sum_{i,s'} \widetilde{p}_{is'} t_{is'j} \widetilde{q}_{is'j}{}^{\circ}(p_{is'j}^B q_{is'j}^B)} \Bigg)\end{aligned} \tag{24}$$

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

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

Figure 5: Global emission changes



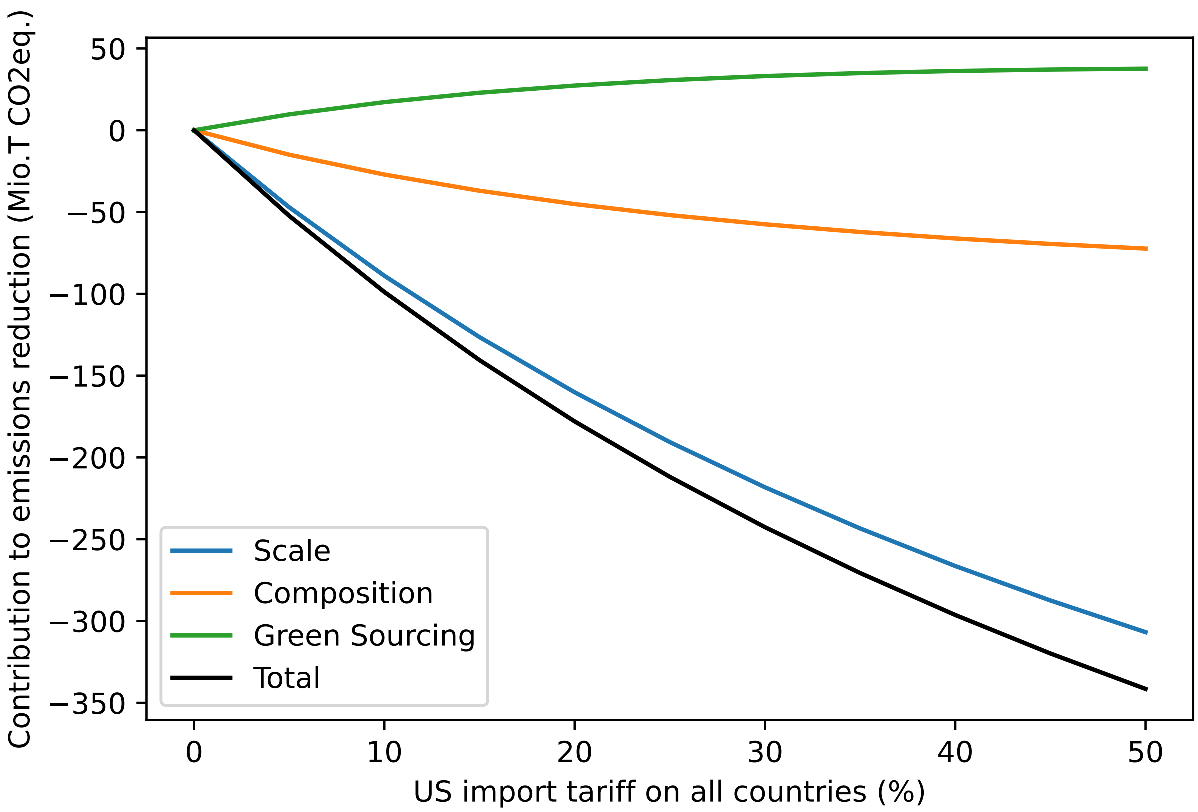
Note: This graph shows the change in global emissions for each scenario (e.g. US1060Retal: The US imposes a 10% tariff on all countries and 60% on China, each country retaliates against the US, but no other tariffs are imposed).

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.

F Additional Graphs

Figure 6: Global emission changes



Note: This graph shows the change in global emissions for different levels of unilateral tariffs imposed by the US.