Trump, Trade, and Emissions*

Simon Lepot† Marcos Ritel‡ Dora Simon§

This version: February 20, 2025 Latest version

Abstract

This paper examines the unintended impact of noncooperative tariff hikes on global greenhouse gas emissions. Using a multi-country, multi-industry quantitative trade policy model, we assess scenarios of protectionism and retaliation informed by the current geopolitical landscape and explore how these policies reshape the carbon footprint of international trade. Our findings indicate that while distortionary tariffs reduce overall domestic economic activity and, consequently, emissions, noncooperative tariff hikes followed or not by retaliation reconfigure trade networks in ways that increase reliance on carbon-intensive production. Thus, contrarily to efficient climate policies, which can unlock environmental gains from trade, 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.

†University of Zurich

‡Kuehne Logistics University.

§University of Stavanger

1 Introduction

The outcome of the 2024 U.S. presidential election has reignited debates over the future of global trade policy, increasing the likelihood of stricter noncooperative measures in the near term. This includes the potential implementation of discretionary tariff hikes, which are likely to trigger retaliatory responses from trade partners. As a result, trade policy is poised to play an even more influential role in shaping the global economic landscape. While these measures are primarily designed to advance strategic and economic interests, they also reshape sourcing decisions which can have long term impacts (Cox, 2021). These shifts in production patterns inadvertently alter the carbon footprint of global production—an environmental consequence that remains largely overlooked in climate policy discussions.

In this paper, we examine the unintended environmental consequences of noncooperative tariff hikes using a modern quantitative framework. We employ a multi-country, multi-industry trade 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 develop a decomposition inspired by the scale-composition-technique approach widely used in environmental economics. 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 the cross-country pattern of production alter the carbon footprint of international trade.

We explore multiple scenarios informed by the current trade policy debate on the aftermath of the U.S. 2024 presidential election to understand the environmental consequences of noncooperative tariffs. We consider both unilateral tariffs, where the United States imposes tariffs without retaliation, as well as scenarios with retaliation from key trade partners.[1] Importantly, this study does not focus on the environmental consequences of a full-fledged tariff war that would arise from the strategic interaction of noncooperative governments, focusing instead on the direct implications of these exogenous policy shifts for greenhouse gas emissions.[2]

Results indicate that while distortionary noncooperative tariffs reduce global production—and consequently, global emissions—they also restructure trade networks in ways that increase reliance on carbon-intensive production. To see this point, note that unilateral tariffs initially improve the protectionist country's terms of trade, generating a real income gain at the expense of trade partners. However, retaliatory tariffs from other countries erode any advantage of protectionism, leading to a net decline in global output and, in turn, in aggregate greenhouse gas (GHG) emissions.

Although these trade policies are not designed as climate measures, they nevertheless result in a modest reduction in global emissions, ranging from 0.2% to 0.9%. A decomposition of this effect into scale, composition, and green sourcing reveals two key insights. First, the primary driver of emissions reduction is the scale effect, as tariff-induced price increases suppress economic activity globally.

Second, a negative green sourcing effect offsets emissions reductions by shifting production toward more carbon-intensive suppliers. For example, when the U.S. imposes a uniform tariff on all imports, global trade increasingly depends on carbon-intensive sectors, such as basic metals and energy, from high-emission producers like India and China. This shift comes at the expense of sourcing from the U.S. and its major trade partners, such as Mexico and

[1] 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 set of few sectors (US10Sectors). All of these have a retaliation equivalent where each country imposes the same tariff against the US. Other tariffs are not affected. These scenarios are indicated with "Retal" in the scenario name.

[2] Ossa (2014) and Lashkaripour (2021) provide estimates for Nash tariffs that would prevail under a generalized tariff war using a quantitative trade model. In line with our results, they show that this equilibrium is associated with sizable welfare losses for participants. Moreover, Ossa (2014) provides estimates of optimal tariffs and show that they are increasing in country-size.

Canada, illustrating how supply chain linkages amplify these effects. This result holds across all scenarios we examine and remains robust to variations in tariff levels under unilateral U.S. taxation.

Notably, this pattern runs counter to the environmental gains from trade that arise when production specializes according to environmental comparative advantage—an outcome that emerges when environmental externalities are correctly priced (Le Moigne et al., 2024). By distorting trade flows, U.S. tariff policy undermines these potential environmental benefits, reinforcing reliance on carbon-intensive production rather than fostering cleaner global sourcing.

This paper contributes to several strands of the literature. There are a few papers analyzing the environmental gains from trade (Shapiro, 2016; Le Moigne et al., 2024). Closer to our analysis is Le Moigne et al. (2024), which uses a similar quantitative setting and decomposition of changes in GHG emissions to study how carbon policies can unlock environmental gains from trade by inducing specialization according to environmental comparative advantages. Contrary to those studies, our analysis focuses instead on the unintended consequences of trade policy. Shapiro (2021) shows that tariffs are lower for dirty industries, thereby serving as an implicit subsidy for carbon emissions.

The recent shift toward protectionism has sparked a wave of studies examining the effects of trade policy on the US economy and politics. Autor et al. (2020) document how trade-exposed counties have shifted their voting behavior toward extreme parties. Evaluating the 2018 trade war, they find that while U.S. tariffs aimed to protect domestic industries, they had no impact on employment. In contrast, retaliatory tariffs by China negatively affected U.S. employment, yet trade-exposed regions still leaned Republican (Autor et al., 2024). Thus, despite being economically harmful, U.S. import tariffs appear to achieve political objectives by securing votes. Another key feature of the 2018 trade war is the issue of tariff pass-through into consumer prices. Earlier studies reported incomplete pass-through rates, suggesting that tariffs were not fully reflected in consumer prices. However, evidence from the 2018 trade war indicates a pass-through rate close to 1 (Flaaen et al., 2020; Houde and Wang, 2023; Amiti et al., 2020), with prices of targeted imports failing to decrease (Fajgelbaum et al., 2020). These dynamics imposed significant costs on importing firms and consumers (Amiti et al., 2019), resulting in a welfare loss of approximately 3% for the US. Looking ahead, Clausing and Lovely (2024) estimate that Trump's new tariff proposals could increase consumer costs by an additional 1.8% of GDP. Our results on US welfare losses are of a similar magnitude.

Only few studies exist on the effect of a US trade war on other countries. Berthou et al. (2018) find that a global 10 percentage points increase in tariffs could reduce the level of global gross domestic product by almost 2%, and up to 3% after two years. Third countries would have to expect currency depreciations against the USD and a lower performance of global stock markets (Carlomagno and Albagli, 2022). Some of the third countries could benefit from a trade war due to trade diversion, meaning that trade would be redirected to them (Rotunno, 2024). This might have happened to the EU in the US-China trade war (Bolt and Mavromatis, 2019). In a trade war involving the entire world, a cascade of effects might happen: Worldwide prices might increase because of the tariffs. This leads to inflationary pressures, to which the central banks respond by increasing interest rates. Firms would react by decreasing their capital demand, and investment and consumption would decrease (Berthou et al., 2018). Obst et al. (2024) find that a unilateral US tariff would increase US GDP in the long run, but retaliation from China decreases US GDP. We contribute by analyzing the economic impact of Trump's 2024 trade policy suggestions in terms of real income for all countries.

2 Choice of scenarios

This section explains the rationale behind the scenarios studied in the report. We analyze five scenarios in which the US unilaterally imposes a policy, and add one retaliation scenario

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

for each in which the trading partners of the U.S. impose tariffs against the U.S. as well. In total, this results in ten scenarios displayed in Table 1. The first scenario assumes that the US levies a 10% tariff on all countries and all sectors. This is based on statements by Trump during his campaign in 2024 (Business, 2024). In the retaliation equivalent, all other countries also levy a 10% tariff on the US, leaving tariffs with other countries as they are. The next scenario extends the first by including a 10% tariff on all countries and a 60% tariff on China. This is also a reoccurring statement in Trump's campaign (CNBC, 2024). In the retaliation equivalent, all countries retaliate with 10% tariffs on the US, and China retaliates with 60%. The third scenario analyzes a similar situation, except that the EU is now able to negotiate to be exempt from the trade war (tariff of 0). All other countries face a 10% tariff, except for China with 60%. While this scenario is not explicitly mentioned by Trump, it is interesting to analyze the effects for third countries that are not in the EU, like Norway or the UK. Again, each country retaliates with the same tariff rate applied to them in the retaliation scenario. The fourth scenario is similar to the second one, except that the base tariff rate for all countries is now 20% (Today, 2024). China is still subject to 60%, and each country retaliates by reciprocating the tariff they face with the US in the retaliation equivalent.

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.

In our unilateral trade policy scenarios, the US imposes a tariff on all goods in all countries. For the retaliatory scenarios, each country imposes the equivalent tariff on the US, without changing its trade policy towards other countries.

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

$$\sum_{s} L_{js} = L_j \tag{8}$$

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

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, which is exogenous and kept fixed in counterfactuals.[3]

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

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

with $e_{is'}$ denoting the exogenous production emission intensity of production of good s' in country i. Note that due to data restrictions, $e_{is'}$ is calculated in terms of tons of CO2 emitted per \$ of output. 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).

3.3 Decomposition

To help us understand the effect of trade policy 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 (Grossman and Helpman, 1995; Copeland and Taylor, 2003; Levinson, 2009; Shapiro and Walker, 2018). This decomposition is similar to the one employed by Le Moigne et al. (2024) to study the environmental gains from trade led 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

[3] President Donald Trump often argues that trade policy should be used as a tool to decrease US bilateral trade deficits. As the deficit in our model is policy-blind, we cannot account for this mechanism in the analysis. Alternatively, we compute results allowing changes in the deficit to be proportional to tariff-led changes in income and verify that this does not impact our results. Notice that fully endogenizing the trade deficit would require a dynamic setting, which is beyond the scope of this paper.

quantity. Switching to trade volume instead of trade flows allows us to write the decomposition in real terms.

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. [4]

Applied to our model, equation (10) captures that trade policy reduces emissions for three reasons. First, tariffs reduce aggregate expenditure by making all goods more expensive - this is the "scale effect". Second, tariffs reallocate aggregate expenditure across industries. As some industries are greener and others are browner, emissions might increase or decrease - this is the "composition effect". Third, tariffs reallocate industry expenditure across countries within the same sector. Similarly, some countries have greener production patterns in a given sector than others - 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. Our decomposition does not include a technique effect because we hold emissions intensities constant.

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

4 Calibration

4.1 Methodology

To bring the model to the data, we apply the "exact hat algebra" method of Dekle et al. (2007), which has become 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 $a_{is'}$ and $b_{is's}$, productivity parameters A_{js}, and iceberg trade costs $\tau_{is'j}$. This approach also guarantees that the model precisely 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 to 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 $\sigma_{s'}$.[5] We keep baseline tariffs of 0.[6]

4.2 Data

We rely on the same data sources as Le Moigne et al. (2024). Trade flow data for both intermediate and final goods come from the OECD Inter-Country Input-Output (ICIO) tables (OECD, 2023). These tables provide a comprehensive representation of the global economy, covering 45 industries and 67 economies—including an aggregate Rest of the World—over the period from 1995 to 2018. While we calibrate the model using the 2018 data, the full dataset is employed to estimate the model's key elasticities, as detailed below.

Greenhouse gas emissions, measured in CO_2 equivalents, are compiled by integrating three sources: the OECD Carbon Dioxide Emissions Embodied in International Trade

[5] Appendices C and D provide a detailed description of the equilibrium conditions in changes and the solution algorithm.

[6] Given that tariffs were not high for our relatively aggregate industries, we do not think this is a strong assumption. We are working on incorporating baseline tariffs into the model.

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 reports CO_2 emissions from fuel combustion across the same 45 industries and 67 economies covered in the OECD ICIO tables.

To broaden emissions coverage and account for non-energy-related sources, we supplement this data with CO_2, CH_4, and N_2O emissions from the other two datasets. Specifically, FAOSTAT provides emissions from agriculture, forestry, and land use, while EDGAR includes emissions from industrial processes, product use, and fugitive emissions. Combined, these datasets capture approximately 93% of global greenhouse gas emissions. Further details on the data integration process are provided in Appendix A.

Although our data offers comprehensive coverage of global production, trade, and trade-related emissions, it has two important limitations. First, our emission intensity calculations rely on trade values rather than trade volumes. Ideally, emissions intensities would be based on volumes, but this is not feasible because the OECD ICIO tables report only trade values, and suitable price deflators at this level of aggregation are unavailable. As a result, in our counterfactual scenarios, changes in emissions capture both shifts in trade volumes and price fluctuations.

Second, we are unable to distinguish emissions intensities by destination. For instance, we must assume that a ton of German steel has the same emissions intensity whether it is consumed in Germany or in the United States. Notably, this assumption aligns with the iceberg formulation of transport emissions embedded in our model. A ton of German steel effectively carries higher embodied emissions when delivered to the U.S. than when used domestically, as a fraction—say, 20%—"melts away" in transit. However, this also raises the price of German steel in the U.S. by the same proportion, ensuring that the emissions intensity remains unchanged.

4.3 Estimation

Following Le Moigne et al. (2024), we estimate the substitution elasticities with the standard approach of ?, 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 B confirm that our estimates fall within the typical range.[7]

5 Results

5.1 Aggregate effects of trade policy across countries

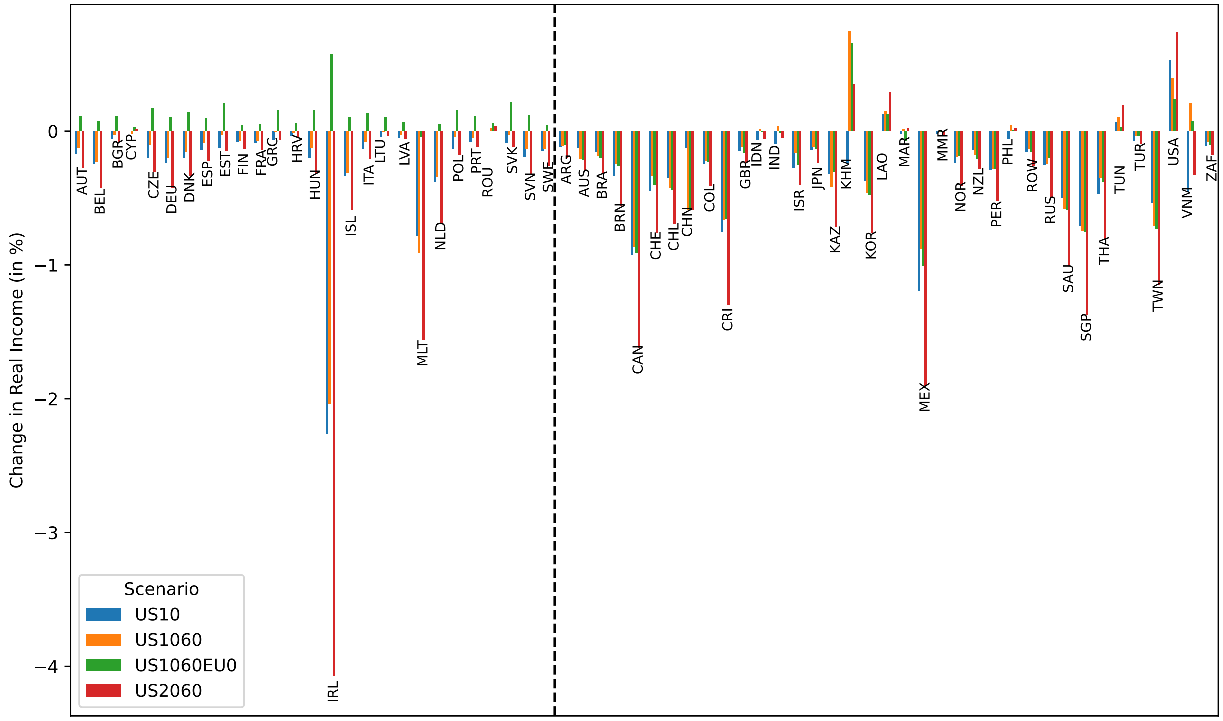
To set the stage for our discussion on the environmental consequences of tariffs, we first outline their economic impact in this subsection, as it serves as the primary underlying mechanism. Figure 1 shows the real income change for each unilateral tariff scenario where no country is allowed to retaliate. The EU countries are shown to the left, all other countries are on the right. The main takeaway is that the US experiences a real income gain in all scenarios, at the cost of real income losses in most other countries and scenarios. Globally, the world would experience a real income loss from each scenario. Specifically, real income increases by around 0.5% in the US for the US10[8] scenario (blue bar). This result follows standard therms-of-trade gains from trade policy, widely described in the literature (Bagwell and Staiger, 1999).

The scenario with 20% tariffs (red bars) leads to the largest gains for the US and the largest losses for most other countries. In the case where the EU is granted an exemption from the tariffs (green bars), each EU country also experiences a real income gain. Some of

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

[8] US10: The US puts a tariff of 10% on everyone, nobody retaliates.

Figure 1: Real Income Changes Unilateral Scenarios



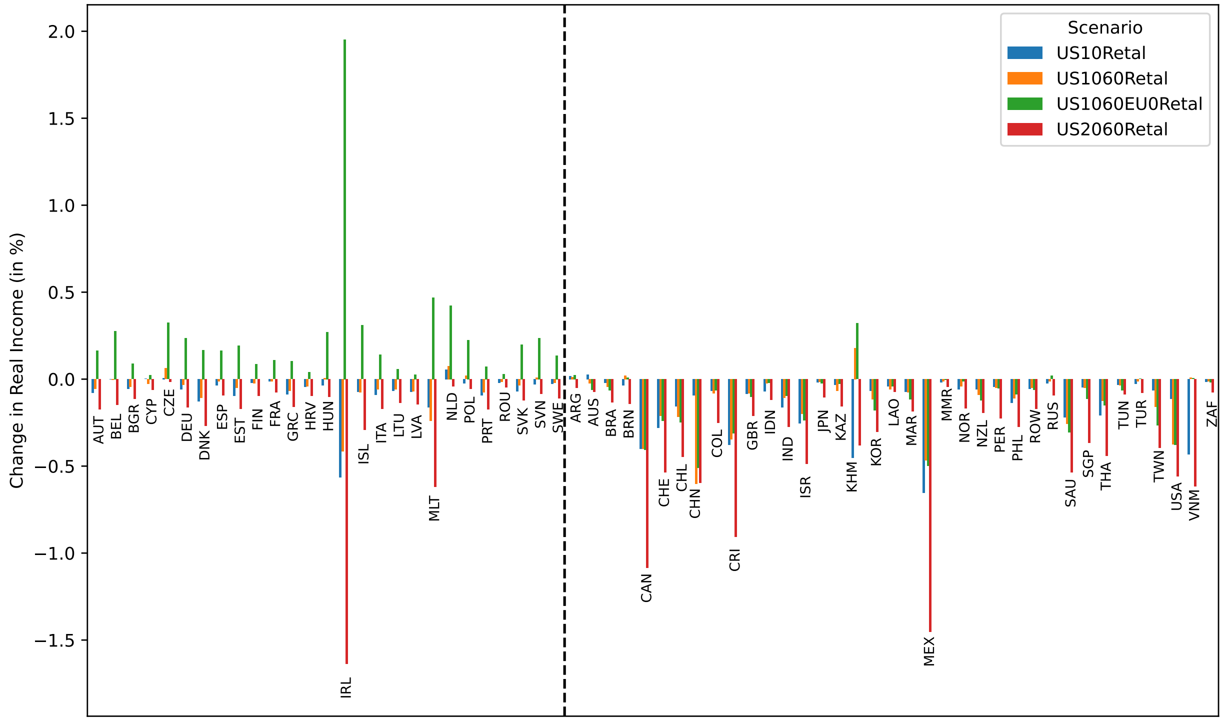
Note: This graph shows the change in real income for each unilateral scenario (e.g. US1060: The US imposes a 10% tariff on all countries and 60% on China, nobody retaliates).

the main trading partners of the US (Canada, Mexico, Great Britain, Ireland) experience a strong decrease in real incomes. Cambodia (KHM) even gains from the policy, but only when China is taxed more than other countries. This indicates that Cambodia can take some of China's market share. Ireland and Malta are often considered tax havens, where many US companies are located. A tax on these countries would reduce exports to the US, and thus lead to a large decrease in the real income (up to 3% in the red US2060[9] scenario for Ireland). The overall decline in real income reflects the reduction in economic activity caused by tariff-induced increases in cross-country and cross-sector prices.

Figure 2 shows each scenario from Figure 1, but now each country retaliates with the same level of tariffs. For example, if the US puts a 60% tariff on China, China also puts a 60% tariff on the US. All other trading partners of China keep the tariffs they had before, if any. With retaliation, the US now also suffers a real income loss in all scenarios. Interestingly,

[9] US2060: The US puts a tariff of 20% on everyone, 60% on China, nobody retaliates.

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).

the EU countries experience a real income gain in case of an exemption from the policies. Overall, the real income losses are now smaller for all countries than without retaliation since then trade partners can also accrue some of the benefits of protectionism. Ireland for example had a real income loss of around 3% without retaliation in Figure 1. When also putting a 10% tariff on the US in Figure 2, its real income loss is less than half at 1.5% for the US2060[10] scenario. There are a few countries which even have a real income gain in all scenarios now (Czech Republic, Netherlands).

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

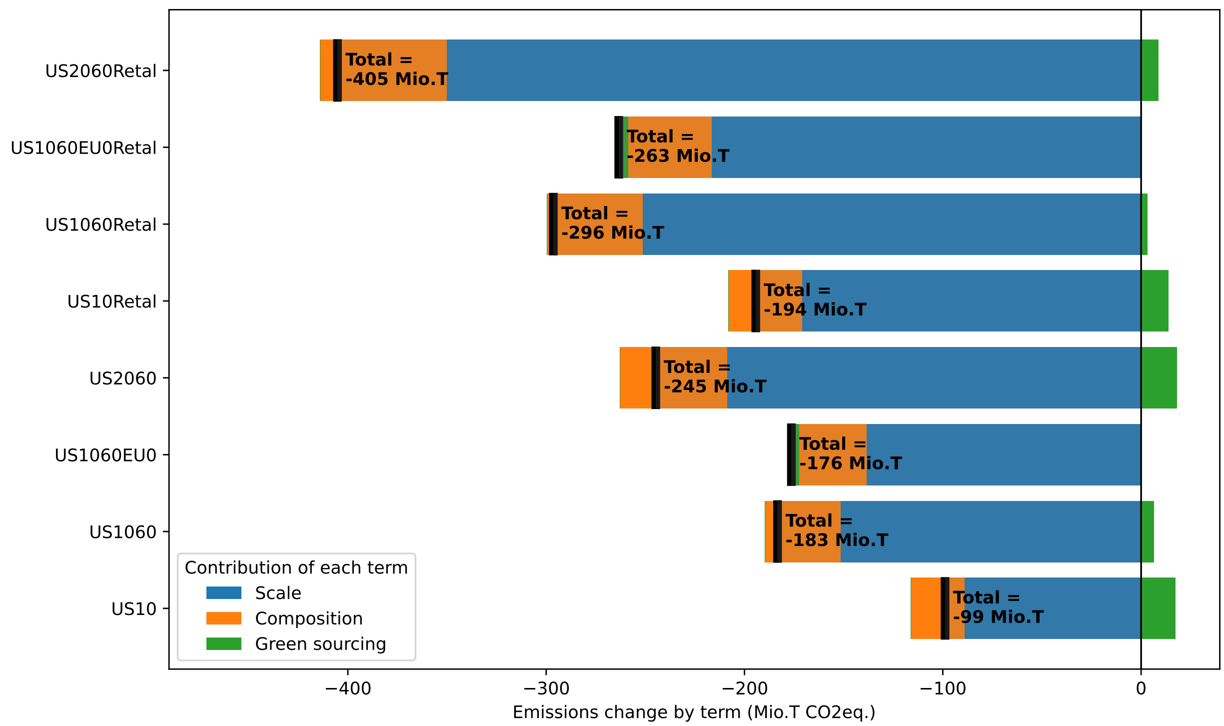
[10] US2060: The US puts a tariff of 20% on everyone, 60% on China, nobody retaliates.

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 decrease in emissions into three effects: scale, composition and green sourcing. The scale effect - the decrease in emissions due to a decrease in economic activity - is responsible for the largest part of the emissions decrease. From a normative perspective, this is the least desirable mechanism for decreasing emissions. Both the composition effect in orange and the green sourcing effect in green would be favorable, as there, economic activity shifts to different sectors or countries as opposed to just declining. Policies that actually target emissions like a uniform global carbon tax (as in Le Moigne et al. (2024)) or tariffs without an environmental bias (as in Shapiro (2021)) lead to small scale effects and large composition and green sourcing effects. With the Trump tariffs, the green sourcing effect even becomes negative. This means that we redistribute economic activity from clean towards dirty countries. Therefore, the Trump tariffs would lead to brown sourcing as opposed to green sourcing and fail to capitalize on the environmental gains from trade. In Appendix Figure 6, we show that this pattern is consistent for different levels of tariffs.

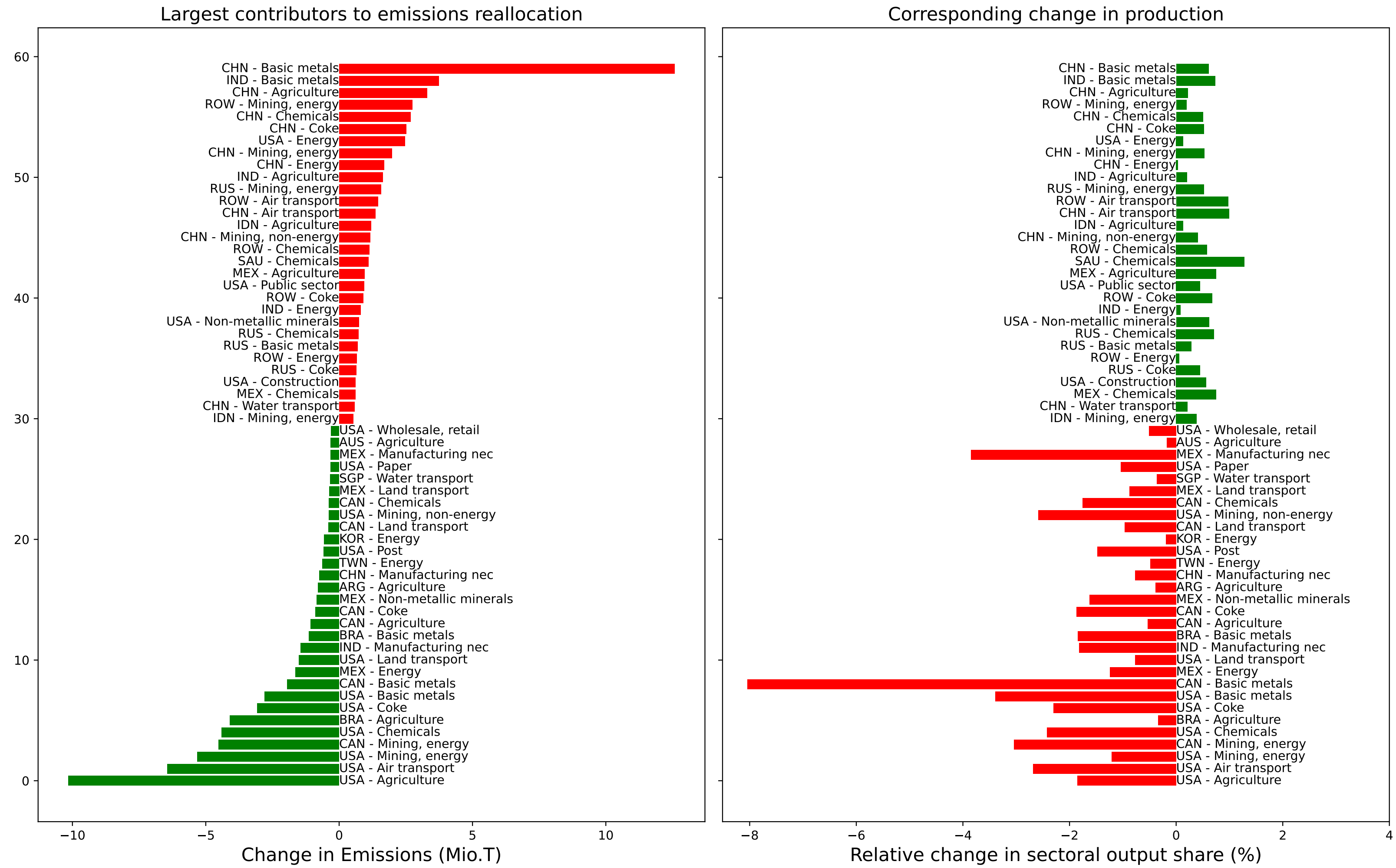
Figure 4 sheds light on the mechanisms for this "brown sourcing" effect in the unilateral US10 scenario. The left panel shows the country-sector pairs with the largest contribution to a change in emissions, where red means an increase in emissions and green a decrease in emissions. The right panel shows the corresponding change in production, where green means an increase in production and red a decrease in production. The first takeaway is that the largest increases in emissions stem from a production increase in sectors with high emissions intensities in low- and middle-income countries like China, India, and Russia. The largest decreases in emissions occur by decreasing production in cleaner countries like the US and Canada. There, large decreases in production like for Canadian basic metals lead to modest decreases in emissions.

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.

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 resurgence of trade policy as a central tool in economic strategy, particularly in light of the 2024 U.S. presidential election, highlights its expanding role in shaping the global economic landscape. This paper shows that while such policies are designed to achieve strategic and economic objectives, there are broader implications on global greenhouse gas emissions. The findings reveal that U.S. tariffs, even without explicit climate considerations, result in slightly decreased global emissions. This decrease in emissions is driven primarily by contractions in economic activity. Crucially, the Trump tariffs lead to a reallocation of economic activity from greener to browner countries of production, thus reversing the environmental gains from trade.

References

Amiti, M., Redding, S. J. and Weinstein, D. E. (2019). The Impact of the 2018 Tariffs on Prices and Welfare, *Journal of Economic Perspectives* **33**(4): 187–210.
URL: *https://pubs.aeaweb.org/doi/10.1257/jep.33.4.187*

Amiti, M., Redding, S. J. and Weinstein, D. E. (2020). Who's Paying for the US Tariffs? A Longer-Term Perspective.

Armington, P. S. (1969). The geographic pattern of trade and the effects of price changes, *IMF Econ Rev 16* **16**: 179.201. Symposium on Growth and International Trade: Empirical Studies.

Autor, D., Beck, A., Dorn, D. and Hanson, G. H. (2024). HELP FOR THE HEARTLAND? THE EMPLOYMENT AND ELECTORAL EFFECTS OF THE TRUMP TARIFFS IN THE UNITED STATES, *NBER working paper 32082* .

Autor, D., Dorn, D., Hanson, G. and Majlesi, K. (2020). Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure, *American Economic Review*

110(10): 3139–3183.

URL: *https://pubs.aeaweb.org/doi/10.1257/aer.20170011*

Bagwell, K. and Staiger, R. W. (1999). An economic theory of gatt, *The American Economic Review* **89**(1): 215–248.

Berthou, A., Jardet, C., Siena, D. and Szczerbowicz, U. (2018). Costs and consequences of a trade war: a structural analysis, (72).

Bolt, W. and Mavromatis, K. (2019). The global macroeconomics of a trade war: The EAGLE model on the US-China trade conflict.

Business, F. (2024). Video on tariffs.

URL: *https://www.fox-business.com/video/6334380407112*

Caliendo, L. and Parro, F. (2015). Estimates of the trade and welfare effects of nafta, *The Review of Economic Studies* **82**(1 (290)): 1–44.

Carlomagno, G. and Albagli, E. (2022). Trade wars and asset prices, *Journal of International Money and Finance* **124**: 102631.

URL: *https://linkinghub.elsevier.com/retrieve/pii/S0261560622000341*

Clausing, K. A. and Lovely, M. E. (2024). Why Trump's Tariff Proposals Would Harm Working Americans, *SSRN Electronic Journal* .

URL: *https://www.ssrn.com/abstract=4834397*

CNBC (2024). Trump floats more than 60

URL: *https://www.cnbc.com/2024/02/04/trump-floats-more-than-60percent-tariffs-on-chinese-imports.html*

Copeland, B. R. and Taylor, M. S. (2003). *Trade and the Environment: Theory and Evidence*, stu - student edition edn, Princeton University Press.

URL: *http://www.jstor.org/stable/j.ctt5hhnzk*

Cox, L. (2021). The long-term impact of steel tariffs on us manufacturing, *Yale University,(cit. on p. 7)* .

Dekle, R., Eaton, J. and Kortum, S. (2007). Unbalanced trade, *American Economic Review* **97**(2): 351–355.

European Commission, J. (2023). Emission database for global atmospheric research (edgar). Joint Research Centre (JRC)/Netherlands Environmental Assessment Agency (PBL), release version 4.tox2 global gridmaps.
URL: *https://edgar.jrc.ec.europa.eu/*

Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J. and Khandelwal, A. K. (2020). The Return to Protectionism, *The Quarterly Journal of Economics* **135**(1): 1–55.
URL: *https://academic.oup.com/qje/article/135/1/1/5626442*

FAO (2023). Faostat emissions totals. License: CC BY-NC-SA 3.0 IGO. Accessed: April 15, 2024.
URL: *https://www.fao.org/faostat/en/data/GT*

Flaaen, A., Hortaçsu, A. and Tintelnot, F. (2020). The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines, *American Economic Review* **110**(7): 2103–2127.
URL: *https://pubs.aeaweb.org/doi/10.1257/aer.20190611*

Fontagné, L., Guimbard, H. and Orefice, G. (2022). Tariff-based product-level trade elasticities, *Journal of International Economics* **137**: 103593.

Grossman, G. M. and Helpman, E. (1995). Trade wars and trade talks, *Journal of Political Economy* **103**(4): 675–708.

Houde, S. and Wang, W. (2023). The Incidence of the U.S.-China Solar Trade War.
URL: *https://www.ssrn.com/abstract=4441906*

Lashkaripour, A. (2021). The cost of a global tariff war: A sufficient statistics approach, *Journal of International Economics* **131**: 103419.

Le Moigne, M., Lepot, S., Ossa, R., Ritel, M. and Simon, D. Z. (2024). Greening ricardo: Environmental comparative advantage and the environmental gains from trade, *WTO Staff Working Paper ERSD-2024-07*, WTO, Geneva.
URL: *https://hdl.handle.net/10419/306822*

Levinson, A. (2009). Technology, International Trade, and Pollution from US Manufacturing, *American Economic Review* **99**(5): 2177–2192.

Obst, T., Matthes, J. and Sultan, S. (2024). What if Trump is re-elected?, *IW-Report* .

OECD (2021). Trade in embodied co2 (teco2) database. Accessed: April 15, 2024.
URL: *https://www.oecd.org/sti/ind/carbondioxideemissionsembodiedininternationaltrade.htm*

OECD (2023). Oecd inter-country input-output database. Accessed: April 15, 2024.
URL: *http://oe.cd/icio*

Ossa, R. (2014). Trade wars and trade talks with data, *American Economic Review* **104**(12): 4104–46.

Rotunno, L. (2024). Trade Policy and Jobs in Vietnam, *IMF Working Papers* **2024**(263): 1.
URL: *http://dx.doi.org/10.5089/9798400296895.001*

Shapiro, J. S. (2016). Trade Costs, CO2, and the Environment, *American Economic Journal: Economic Policy* **8**(4): 220–254.

Shapiro, J. S. (2021). The Environmental Bias of Trade Policy, *The Quarterly Journal of Economics* **136**(2): 831–886.

Shapiro, J. S. and Walker, R. (2018). Why is pollution from us manufacturing declining? the roles of environmental regulation, productivity, and trade, *American Economic Review*

108(12): 3814–54.

URL: *https://www.aeaweb.org/articles?id=10.1257/aer.20151272*

Today, U. (2024). Donald trump's proposed 20

URL: *https://eu.usatoday.com/story/news/politics/elections/2024/08/15/donald-trump-twenty-percent-tariff-economic-policy/74809155007/*

A 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.[11] 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.[12] 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

[11] 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'

[12] 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.[13]

B Elasticity Estimation

Table 2: Elasticities Summary Statistics

N	Mean	SD	Min	Max
42	3.61	0.86	1.78	5.86

[13]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.

C 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:

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

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

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

D 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:

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

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 :

$$\widetilde{I}_j I^B_j = \sum_s \widetilde{E}_{js} L^B_{js} w^B_j + \sum_{i,s'} \widetilde{I}_j \widetilde{p}_{is'} t_{is'j} \widetilde{q}_{is'j} {}^\circ (p^B_{is'j} q^B_{is'j}) + \sum_{i,s',s} \widetilde{E}_{js} \widetilde{p}_{is'} t_{is'j} \widetilde{m}_{is'js} {}^\circ (p^B_{is'j} m^B_{is'js}) + D^B_j \tag{22}$$

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

We then use (22) in (23):

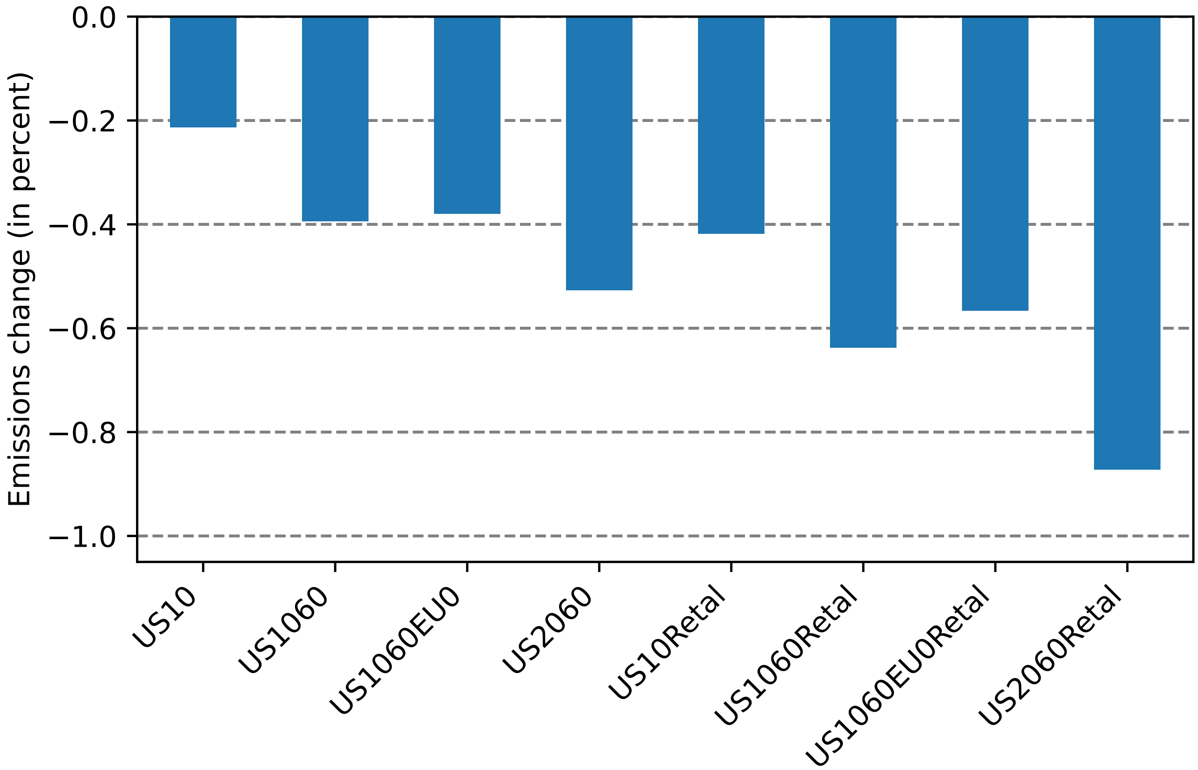
$$\begin{aligned} \widetilde{E}_{is'} E^B_{is'} = \widetilde{p}_{is'} \Bigg(& \sum_{j,s} \widetilde{E}_{js} \left[\widetilde{q}_{is'j} {}^\circ (p^B_{is'j} q^B_{is'j}) \frac{L^B_{js} w^B_j + \sum_{i,s'} \widetilde{m}_{is'js} {}^\circ \widetilde{p}_{is'} t_{is'j} (p^B_{is'j} q^B_{is'j})}{I^B_j - \sum_{i,s'} \widetilde{q}_{is'j} {}^\circ \widetilde{p}_{is'} t_{is'j} (p^B_{is'j} q^B_{is'j})} + \widetilde{m}_{is'js} {}^\circ (p^B_{is'j} m^B_{is'js}) \right] \\ & + \sum_j \frac{D_j \widetilde{q}_{is'j} {}^\circ (p^B_{is'j} q^B_{is'j})}{I^B_j - \sum_{i,s'} \widetilde{p}_{is'} t_{is'j} \widetilde{q}_{is'j} {}^\circ (p^B_{is'j} q^B_{is'j})} \Bigg) \end{aligned} \tag{24}$$

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

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

Figure 5: Global emission changes

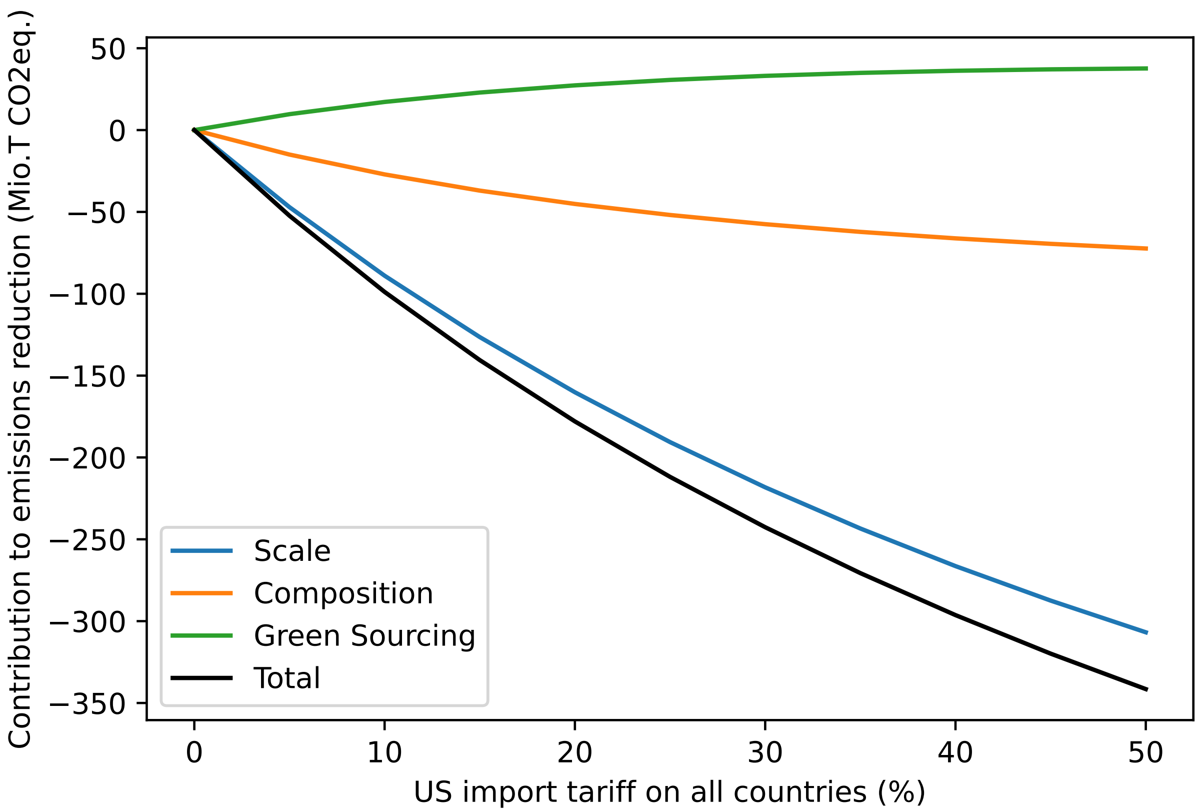


Note: This graph shows the change in global emissions for each scenario (e.g. US1060Retal: The US imposes a 10% tariff on all countries and 60% on China, each country retaliates against the US, but no other tariffs are imposed).

$\alpha(\widetilde{E}_{\text{sol}}, \widetilde{p}_{\text{sol}})$ 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.

E 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.