CO2 Emission and Trade Policy in Agricultural and Food products

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Abstract

Agri-food system is one of the economic sectors most at risk from climate change, but it is also a significant contributor to it, with greenhouse gas emissions (GHG) from the food supply chain equal to one-third of the global anthropogenic total in 2018 (Tubiello et al. 2021). Specifically, crop and livestock production within the farm gate contributes more than 50% of the methane (CH_4) and 75% of the nitrous oxide (N_2O) emissions from human activity globally (FAO, 2020). This paper relies on the recent work of Shapiro (2021) that firstly analysed the nexus between pollution embodied in traded goods, against the actual structure of trade policy (tariffs or non-tariff measures-NTMs). In our contribution we focus on agricultural and food products, considering three main pollutants (CO_2, CH_4, N_2O), with the aims of answering the following research question: are actual trade policies a tax or a subsidy to total CO_2 (equivalent) emissions embedded in agri-food imported goods? Main findings suggest that for all the three pollutants investigated a negative implicit carbon tax is applied, i.e. on average countries applied an implicit subsidy on more pollutant imported goods. This estimated implicit subsidy to CO_2 emissions imported in agri-food products tend to be higher when also the ad-valorem equivalent of non-tariff measures (NTMs) is accounted for. By investigating the country-group heterogeneity in the applied tax or subsidy to imported CO_2, results show that the larger implicit subsidy is applied by the trade policy structure of European Union countries. Specifically, Western and Northern European countries have among the largest negative environmental biases in trade policy, while more polluting countries, like China, India, Russia, Brazil and Mexico, tend to apply smaller (implicit) subsidies.

Keywords GHG emissions, Trade policy, Environment, Agricultural and Food imports

JEL code F6, F13, F18, Q17, Q18, Q50, Q56

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1. Introduction

When dealing with anthropogenic climate change, and especially with the contribution of economic activities to global Green House Gases (GHGs) emissions, one of the most debated issues concerns the relationship between international trade and the environment. A large body of literature emphasizes the ambiguous role of trade, which can be either beneficial or detrimental for the environment. Within this framework, policies play a key role in shaping such a relationship (Copeland et al., 2021). On the one hand, increasing exposure to international trade may affect countries' decisions on whether or not tightening up domestic environmental policies, as a form of trade protection. On the other hand, trade policies may either enhance environmental degradation, or can be used to protect the environment. Against this background, a key issue is whether policies of the last 30 years encouraging progressive global trade integration have promoted environmental degradation (Copeland et al., 2021). A recent contribution by Shapiro (2021) tries to answer this question, providing evidence that the structure of global trade protection has generated an implicit subsidy to trade dirtier goods. Shapiro (2021) provides compelling evidence that tariffs and non-tariff barriers (NTBs) are considerably lower in dirtier goods, and especially in more "upstream" goods, namely in those products more distant from the final consumption (see Antràs et al., 2012). Therefore, trade policies have generated over time a side effect, which contributed to considerably increase CO2 emissions, and, thus, fostering climate change.

The analysis carried out by Shapiro (2021) covers 50 manufacturing industries for the year 2007. However, it is worth noticing that when agricultural goods and manufactured food products are removed from his sample, the estimated effects reduce their statistical significance, or they even turn non-significant when tariffs are concerned (see Appendix Table I, line 25). This finding may suggest that the role played by the global trade protection structure of the agri-food system may be of some importance in this context. Building on this simple conjecture, in this paper we investigate whether the global structure of trade protection of the agri-food sector hampers or promotes CO2 emissions of imported agricultural and food products.

Our focus on the agri-food sector is motivated by the following stylize facts. First, trade protection in terms of tariffs and NTMs are systematically higher in the agri-food than in other tradable sectors. Second, on the one hand, the agri-food is one of the economic sector most affected by climate change and, on the other hand, it is also a significant contributor to it, with greenhouse gas emissions from the food supply chain equal to one-third of the global anthropogenic total in 2018 (Tubiello et al. 2021). According to the IPCC (2014), CO2 accounts for 76 percent of global greenhouse gas emission, methane (CH4) accounts for 16 percent and nitrous oxide (N2O) for 6 percent. If the use of fossil fuels for energy generation is the single largest source of carbon dioxide emission, the agricultural sector is the major source of anthropogenic methane emissions, as it accounts for around a quarter of total emissions, closely followed by the energy industry (IEA 2020). The same holds when considering nitrous oxide. More specifically, crops and livestock production within the farm gate contribute more than 50% to the global methane (CH4) emission and for about 75% of the nitrous oxide (N2O) emissions (FAO, 2020). Against this background, the agri-food sector should clearly play a relevant role in GHGs mitigation strategies.

Our empirical analysis built from Shapiro (2021). However, we depart form this relevant paper in a number of important dimensions. First, our analysis does not focused only on CO2 emission, but focused on three relevant pollutants for the agri-food sector: Carbon dioxide (CO2), the most important greenhouse gas emitted from the use of fuel combustion; nitrous oxide (N2O), mainly emitted from agriculture and to a lesser extent industrial activity; methane (CH4), primarily released from agriculture and natural gas processing.

Second, on the specific agri-food sector, we distinguish the emission rates of 25 different agricultural and food products. Third, we use more recent and extended estimates of the ad-valorem equivalents (AVEs) of NTMs proposed by Niu et al (2018). Last, but not least, in our estimation we used information from trade policy based on country tariff lines for seven years of data, allowing a more precise estimation of the implicit carbon tax measure.[1] Furthermore, instead of using a cross-section of countries, our estimates of the implicit CO2 tax/subsidy rate is based on a panel dataset.

The main findings are in line with those of Shapiro (2021) and suggest that for all the three pollutants under investigation a negative implicit carbon tax is applied, i.e., a negative carbon tariff or a positive carbon subsidy. These estimated carbon subsidy is, on average, higher when non-tariff measures (NTMs) are accounted for. When considering the heterogeneity of the main results across different geographical areas, we find larger implicit subsidy to CO2 for European countries. Specifically, Western and Northern European countries have among the largest negative environmental biases in trade policy, while more polluting countries, like China, India, Russia, Brazil and Mexico, tend to apply smaller subsidies.

The remainder of this paper is organized as follows. The next section provides the background of this paper. Sections 3 and 4 present the data and the methodology used for the empirical analysis. Finally, Sections 4 and 5 discuss the main results and conclude.

2. Background

The role played by international trade in affecting the environment is highly contentious. Such a relationship has been investigated so far especially considering how trade liberalization can affect the environment through the perspectives of the comparative advantage and economic growth (Cherniwchan et al., 2016). On the one hand, the existence of differences in the strictness of environmental regulations across countries may be seen as source of comparative advantage, leading the production of dirtier goods to be shifted from high- to low-regulation countries, the so-called *pollutions havens* (Copeland and

[1] Shapiro (2021) utilizes AVE of NTMs data from Kee et al (2009). These NTB values are calculated for each six-digit HS code, but for a single year around 2000–2003.

Taylor, 2004). On the other hand, international trade may positively affect the environment, through an increase in countries' economic growth (Copeland and Taylor, 2004), following the mechanism highlighted by the well-known Environmental Kuznet Curve (Grossman and Krueger, 1993).

More in general, there is a large and growing body of literature studying the effect of increasing trade exposure on the environment, which touches several aspects. A recent review by Copeland et al. (2021) contributes in shedding new light on this topic. The authors present nine relevant stylized facts describing the relationship between globalization and environment. From these facts it clearly emerges that trade patterns are core to the environmental debate. However, the authors reach the conclusion that despite the growing emphasis on this topic, and the availability of new data and tools, there is not conclusive evidence on whether trade is beneficial or detrimental for the environment.

Within this framework, the review highlights that policies play a key role in affecting the relationship between trade and environment. On the one hand, an increase in the domestic competitive pressure due to the progressive trade integration, may lead some countries to weaken their environmental regulation, especially when trade agreements do not allow the use of subsidies and as a consequence environmental policies may be used (*race to the bottom hypothesis*). On the other hand, trade policies may either promote or harm the environment. This is due to the fact that countries may use trade policies to protect domestic environmental outcomes, by imposing trade restrictions to preserve the environment. On the other hand, trade policies may (unintentionally) promote trade of polluting goods, and thus damaging the environment. Shapiro (2021) presents compelling evidence of this last hypothesis, giving a fundamental contribution to this strand of literature. Importantly, Shapiro (2021) demonstrated that the phenomenon described in his paper is "unvoluntary", a side effect of the process through countries set their optimal trade policy. In fact, one of the potential explanations of this stylized fact is related to the level of industries' *upstreameness*. The level of *upstreamness* is associated with the position of an industry's output along the vertical product chain, and thus with the distance of a production from final consumers (Antràs and Chor 2013). More upstream goods are quite far from the final consumption, while more downstream industries are close to the final consumption. However, and importantly, more upstream industries are on average dirtier than downstream industries, as the combustion of fossil fuels is directly involved in the manufacturing of goods that are then mainly sold as input to other industries. As a result, upstream products are dirtier than their downstream counterparts. This fact is of relevant importance to explain the results in Shapiro (2021), as more upstream industries are, on average, associated to lower trade protection. Such a difference in trade protection has a potential explanation on the political economy of trade protection. Final consumers are much less organized than producers (Olson, 1965). Therefore, firms downstream exert a strong lobby to have high trade protection on the goods they produce, and, at the same time, lower protection for the inputs they use for the production, resulting in the so-called tariff escalation, i.e. the level of protection tend to rise moving from up-stream (and more polluting) to dawn-stream (and less polluting) consumer goods.

3. Empirical strategy

To measure differences in trade policy between industry's 'dirtiness', defined considering CO2 emissions per euro of output, the estimated equation is:

$$T_{j,s,t} = \alpha\, CO_2(\mathrm{Eq})_{j,s,t} + \gamma_j + \lambda_t + \varepsilon_{j,s,t} \qquad (1)$$

where $T_{j,s,t}$ is the mean import tariff or the ad valorem equivalent of NTMs that destination country j imposes on imported good s, in year t [2]; $CO_2(\mathrm{Eq})_{j,s,t}$ is the tons of CO2 equivalent emitted per euro of (country j) imports of product s in year t, γ_j and λ_t are (importer) country and time fixed effects, respectively. Destination country dummy γ_j implies that the regression compares trade policy across goods within a country. The idiosyncratic error $\varepsilon_{j,s,t}$ contains all un-modeled determinants of import tariff rates (or NTMs).

We focus on three relevant pollutants in agriculture and food productions: Carbon dioxide (CO2), nitrous oxide (N2O), methane (CH4).[3] To express all the emissions with a unique measurement unit - the total CO2 equivalent - any different pollutant is multiplied by its Global Warming Potential, as given by the IPCC Fourth Assessment Report. Thus, for example, the tons of CH4 emitted per euro of Italian imports of cattle meat in year t is measured as the mean of emission from cattle meat production in all the partner countries from which Italy imports that product, weighted by Italian imports of cattle meat, and expressed as CO2 equivalent.[4]

The total emissions of single country-product include both direct and indirect emissions for each pollutant. The former accounts for those emitted by country to produce product s, the latter (indirect) those emitted to produce inputs used in the production of s, and in the production of inputs to inputs, and so on.[5]

With equation (1) we do not estimate a causal effect of CO2 intensity on tariffs, as this represents just a descriptive relation showing the covariance of carbon intensity and trade policy within each country (Shapiro, 2021). As a result, the estimated parameter α from Eq. 1 represents the duties collected per ton of CO2 emitted, or the carbon tariff implicit in existing trade policy. Note, if the estimated α is positive

[2] In the analysis tariffs and the ad valorem equivalent of NTMs, we also considered them together to obtain an overall rate of protection applied by each country and sector.

[3] Emissions from agriculture refers to crops and livestock activities (Stadler et al. 2018). Emissions from crops derive from the use of nitrogen and phosphorus as fertilizer; emissions from livestock refer to the emissions produced by the animals, but also by cultivation of feed crops (for detail, see Merciai and Schmidt, 2016).

[4] Note that Exiobase database allows to observe the emission rates for only 44 exporting countries, representing however the 90% of world GDP.

[5] The emission is calculated from inverting an input-output table.

coefficient, then it would imply an additional import duty for each additional ton of CO2 embodied in the imported product; otherwise, a negative estimated α coefficient would represent a carbon 'subsidy' in trade policy.

The estimation of (1) may suffer from a bias due to measurement errors in the CO2 emission intensity. To address this issue, by following the approach undertaken by Shapiro (2021), the equation (1) is estimated using also IV regression, by using direct emissions rate of the 10 smallest countries in the dataset as instrument for (endogenous) total emission. The first stage of the IV regression of equation (1) is:

$$CO_2(\mathrm{Eq})_{j,s,t} = CO_2(\mathrm{Eq})^d_{j,s,t} + \mu_j + \eta_t + \varepsilon_{j,s,t} \qquad (2)$$

where $CO_2(\mathrm{Eq})^d_{j,s,t}$ measures direct emissions reflecting, for example, emissions from producing dairy products but not emissions embodied in inputs used to produce dairy products, such as milk.[6]

4. Data source

To carry out our empirical analyses, data have been gathered from different sources. The variables considered include longitudinal data from pollution emissions, trade flows and trade policy measures. In what follows, we briefly present the main data and their sources.

Emissions data

The emissions rates, reported as tons of CO2 (equivalent) emitted per euro of imported goods, are computed from Exiobase database (3.8.1 version), a time series of detailed environmentally extended multiregional input-output tables that provide data on industry-specific and final demand air emissions for 27 pollutants (see Stadler et al, 2018). These rates account for total emissions, calculated from inverting an input-output table, meaning that both direct and indirect emissions are taken into account.
The database reports data on emission rates from 1995 to 2011 for 44 countries (28 EU member states plus 16 major economies) and five rest of the world regions. Exiobase uses rectangular supply-use tables in a 163 industry by 200 products classification as the main building block. The Exiobase products classification allows to distinguish 15 agricultural products (including forestry and fish products), and 10 food & beverage products and tobacco.[7]

[6] Shapiro (2021) noted that the validity of the instrument could rise concern about the reflection problem. Nevertheless, the possible persistence of measurement error would drive downward the estimated carbon subsidy in trade policies. Moreover, he observed that there are not problems concerning omitted variables and reverse causality because the analysis estimates the covariance of CO2 intensity and trade policy within each country, not a causal effect of CO2 intensity.
[7] The product classification reported by Exiobase matches with GTAP agri-food sector description, although the former allows to split two sectors: 'Cattle, sheep, goats, horses' and 'Meat' giving more detailed product classification.

The 44 Exiobase countries are used as exporting countries of agricultural and food products, which emissions, weighted on trade, are imported by the 188 countries of our final database.[8] As previously reported, equation (1) is estimated also using instrumental variable (IV) regression, with direct emissions rate of the 10 smallest countries in the dataset used as instrument. Direct emissions of each pollutant origin from Exiobase database.

Table 1 describes the direct and total mean emission rate of agricultural and food products, weighted by the value of output. The products are ordered from cleanest to dirtiest based on mean of direct emission rates, expressed in tons of CO2 equivalent per million of euro, of the three pollutants considered. The cleanest five products are mainly food product, with mean global emissions rate of 68 tons of CO2 per million € of output, while the dirtiest five products have a mean global emissions rate of over 5,000 tons of CO2 per million € of output.

Figure 1 shows the mean direct emission rate for each of the 44 Exiobase countries, weighted by the value of agriculture and food product output. Each map reports a single pollutant and shows how the lowest emission intensities are generally reported by European countries. US and Canada present always a medium-high level of emission intensities, while countries of the south of world show always the highest Methane and Nitrous oxide emission intensities. What emerge from these maps is that emission intensities are skewed and that, considering Carbon dioxide, Methane and Nitrous emission, the five dirtiest countries have between 7, 19 and 13 times of the emission intensity of the five cleanest countries, respectively. The large differences in emissions intensities across countries suggest that outsourcing production of dirty products could have important environmental consequences (Copeland et al, 2021).

When direct emissions are considered, food products are relatively cleaner than agricultural products, i.e. their direct emissions are only a small share, always below 10%, of the total emission rates which include emissions embodied in their entire value chain (see table 1). Indeed, by sorting the products by total emission rates we find that, among the dirtiest five products there is again paddy rice, but also its manufactured 'processed rice', which direct emission rate increasing from 413 tons/million€ to 4,474 tons/million€ when measured as total emissions, thus including the emissions of input used; the same is true for 'cattle' and its manufactured 'product of meat cattle', which emission rate raising from 145 to 6,424 tons per million euro of output, when moving from direct to total emission intensity.

Trade and trade policy data

Trade data, used to weight the emissions that are embodied in imported good, come from BACI-CEPII database. BACI (Base pour l'Analyse du Commerce International) is a database from CEPII used in applied trade analysis that publishes statistics on bilateral trade flows at the product level, on yearly

[8] The list of Countries is reported in Table A1 in Appendix. Note that the use of NTMs data reduces to 94 the number of countries.

basis. Bilateral trade data, reported at HS 6-digit, are firstly aggregated at Exiobase/GTAP level using the concordance table, then the data are summed at the importer-product level to measure the share of country-product imports that origin from each of the 44 exporting countries.

Tariff data come from CEPII MAcMaps-HS6 database, which provides the ad valorem equivalent of applied protection for each product importer-exporter at HS 6-digit level for the years 2001, 2004, 2007 and 2010 .[9] To minimize endogeneity problems when aggregating tariff data from HS 6-digit to Exiobase/GTAP level, we rely on the concept of "reference groups of countries", where bilateral trade are replaced by those of the reference group of countries (Bouet et al, 2008).

Non-tariff measures (NTMs) come from Niu et. al (2018) estimates, reported as AVEs of NTM at HS 6-digit level, for 97 countries, for the years 1997, 2000, 2003, 2006, 2009, 2012, 2015.[10] To harmonize tariff and NTM data, we report the AVEs of NTM using the mean between previous and subsequent year data, i.e. the mean between 2000 and 2003 is reported as 2001, between 2003 and 2006 as 2004, and so on. This allows to estimate the ‘implicit carbon tax’ using both tariffs and AVEs of NTM separately or using total trade protection obtained by summing tariff and AVEs NTM.

Throughout all the analysis the years considered are 2001, 2004, 2007 and 2010.

5. Main results

Tables 2 reports results of tariffs (or NTMs) regressions, where the key right-hand side variable of interest is the total CO2 (equivalent) emissions, estimated by distinguishing the three considered pollutants. [11] Odd-numbered columns report OLS estimates of equation (1), even-numbered columns report the IV regressions of tariffs on total CO2 intensity, instrumented by direct CO2 intensity (equation 2).[12] Panel A reports estimates for import tariffs only, Panel B results for AVE of NTMs only, Panel C reports import tariffs plus AVE of NTMs.

As discussed before, the parameter α represents the duties collected per ton of CO2, CH4 and N2O embedded in trade. Thus, a negative value of the coefficient should be interpreted as an implicit subsidy. The results suggest that for all three pollutants a negative implicit carbon tax is applied

Specifically, Panel A shows how global tariffs represent an implicit subsidy in trade policy, that is estimated equal to 3 €/ton, 1 €/ton and 5 €/ton for CO2, CH4 and N2O emissions, respectively. The IV

[9] For some tariffs missing data we made the following little adjustments: for Luxembourg (year 2007 and 2010), we used the Belgian tariff; for the Southern African Customs Union (SACU) composed by Botswana, Lesotho, Namibia, South Africa, and Swaziland we maintain the same duty.

[10] The work of Niu et al (2018), building on Kee et al. (2009), estimates the ad valorem equivalents of NTMs for 97 countries at the product level over the period 1997–2015 using the information on the incidence of NTMs from the UNCTAD-MAST database.

[11] Note that to exclude outliers, we exclude all the values falling above the 99th percentile of each variable.

[12] First stage regressions of total CO2 emission rate on direct CO2 emission rate are reported in Appendix (Table A2).

estimates (see odd-numbered columns) report a dimension of the mean subsidy to pollutants emissions much larger than the corresponding OLS estimates, and equal to 10 €, 8 € and 25 € per ton, respectively. This increase in the estimated coefficients is consistent with attenuation bias in fixed effect estimates.[13] All estimated coefficients are significant, at conventional statistical level.[14]

Panel B of Table 2 reports the implicit carbon tax in AVE of non-tariffs measures. The coefficients are all negative and larger in (absolute) magnitude, highlighting the presence of an implicit subsidy to pollutant emissions also in global AVE of NTMs. Only for CO2 emissions the dimension of this implicit subsidy is comparable to what observed for tariffs, while there is a larger magnitude for CH4 and N2O emissions. Their implicit subsidy almost doubled, reaching 12 €/ton and 45 €/ton respectively (see columns 4 and 6 of table 2). Finally, in Panel C tariffs and NTBs are summed up. The IV regression results, reported on the odd-numbered columns, give an average subsidy to CO2 emissions in trade policy of about 20 €/ton for CO2, of 16 €/ton for CH4, and of about 58 €/ton for N2O emission.

To investigate how these implicit subsidies vary by country, we estimate what reported in Panel C separately for each country.[15] Figure 2 plots the results, obtained using IV specification and by distinguishing the three pollutants. We limit the number of countries reported in figure 2 only to the 44 (relevant) economies included in Exiobase database. Each red point represents the estimated α coefficient derived from single-country regressions; blue dots highlight the position of the 15 countries belonging to the European Union during all the analyzed periods. The countries and their estimated points are ordered by the value of the α coefficient. As a rule of thumb, almost every nation has a carbon subsidy, since almost all the coefficients taken into consideration are negative. Specifically, Western and Northern European countries have among the largest carbon subsidy in trade policy, with subsidies values that changes among the three pollutants and tend to be higher when measured on CO2 equivalent of N2O and CH4 emission rates. The values estimated for the EU15 countries show quite relevant and heterogeneous subsidies in trade policy, that range, for example, from 37€/ton of Ireland to over 200€/ton of Spain when estimated considering N2O emission rate, or from 9€/ton of Spain to 64€/ton of Finland when we consider the CH4 emission rate.

By contrast, Figure 2 shows that more polluting countries like China, India, Russia, Brazil and Mexico tend to apply smaller subsidies, that become even a taxation. The general results observed over all countries of the dataset are in line with Shapiro (2021) global finding. Indeed, large subsidies in trade policy appear in both rich regions like the EU and poor regions like Africa, as well as small subsidies appear in both rich countries like USA and poorer countries like Rwanda (see Figure 1A in Appendix).

[13] The first-stage Kleibergen-Paap F-statistic reported in the table shows that the used instruments are strong, as expected being direct emissions a large part of total emissions.

[14] Note that these results slightly change in magnitude if estimated by reducing the number of importer countries to the only 94 countries that presents AVE of NTMs data.

[15] We use equation (1) and (2), by excluding country fixed effects.

Also, the lack of predictable patterns is consistent with Shapiro (2021) findings, whose interpretation is that these implicit carbon taxes are due to political economy forces that are correlated with CO2 emission rate.

1. Conclusions

This paper relies on the recent work of Shapiro (2021) that firstly compares the measure of pollution embodied in traded goods against the actual structure of trade policy (tariffs or NTMs). By focusing the analysis on the agri-food sector, we check whether trade policy of countries taxes or subsidies the pollution emissions of imported agricultural and food products. Finding suggest that, for all the three pollutants more involved in GHG emission in agriculture, a negative implicit carbon tax is applied. The result can be quantified as an implicit average subsidy of 9.8, 24.5, or 7.7 euro per ton of CO2-equivalent emissions measured for CO2, N2O, and CH4, respectively. These estimated subsidies are higher when AVE of NTMs is considered. We also estimated separately for 44 importer countries (representing the 90% of world GDP), the implicit subsidy on CO2 of imported products induced by the respective the tariff structure. Overall, for the three pollutants, we find large implicit subsidy to CO2 for European countries. Specifically, Western and Northern European countries have among the largest negative environmental biases in trade policy, while more polluting countries, like China, India, Russia, Brazil and Mexico, tend to apply smaller subsidies, or even tax.

These findings have at least two relevant policy implications. The first concerns the potential application and impact of the new trade measure of border carbon adjustments (BCAs). The measure combines environmental and trade policies by levying border adjustments based on the estimated social costs of GHG. As part of a plan to decarbonize its economy by 2050, the European Union is considering the introduction of a BCA mechanism, to reduce the risk of carbon leakage and to level the field for European industries working towards decarbonization of their production processes. However, we observed that countries, and especially European countries, are imposing greater protection on clean than on dirty agri-food products, by creating an implicit carbon subsidy rather than moving to the adoption of a carbon tariff. According to the current Commission's proposal, BCA will begin on 1 January 2023 and will not apply to agricultural products, although in 2026 the Commission will evaluate whether to extend the scope to include other products, and many amendments to include agricultural products have already been presented.

The second implication concerns the "*Farm to Fork-F2F*" Strategy. At the heart of the European Green Deal, the EU wants to redesign its agri-food systems, by supporting a global transition toward environmental sustainability, also through its trade policies. However, the EU import of agricultural products seems destinated to increase as an effect also of F2F (decrease in EU productivity due to the reduction in the use of pesticides and nutrients as well as the increase in organic farming) by 2030.

Hence, as an effect of our findings, showing that current EU trade policies represent an implicit subsidy to the import of more polluting agricultural and food products, the F2F strategy will probably result in a global increase, and not decrease, of total emissions because domestically produced goods will be replaced by imported goods, with high emission intensities. This potential and required reduction in the emissions in European countries could be then compensated from an increase of GHGs emissions in those countries that source these ‘dirty’ products to Europe, a phenomenon known as *carbon leakage*.

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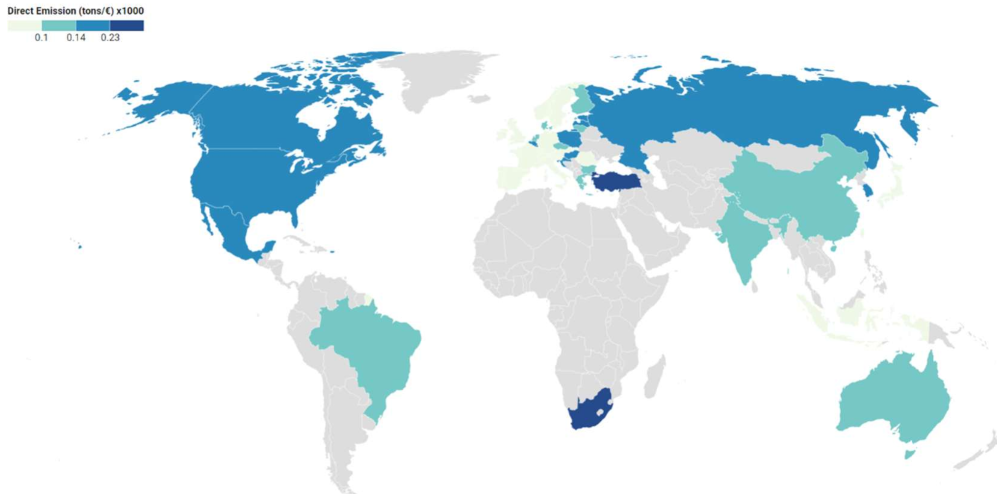
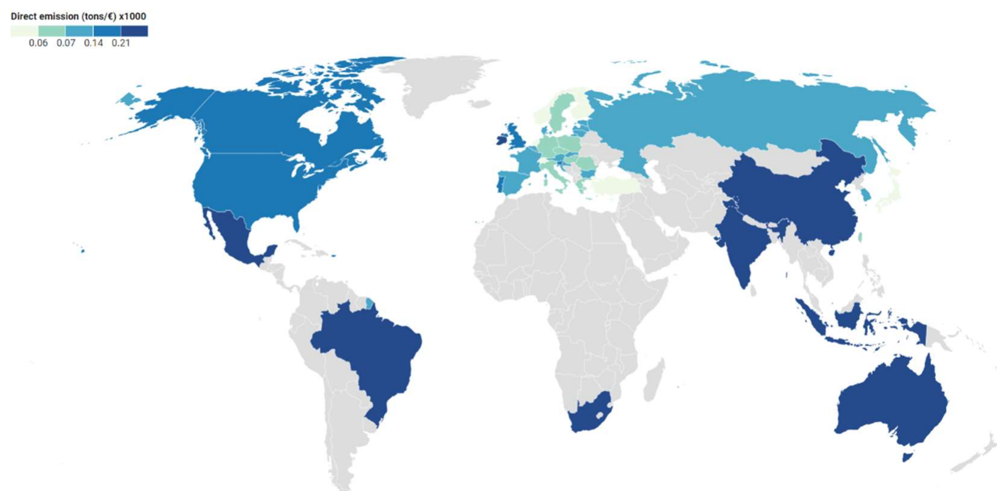
Figure 1 Direct Emission Rate (year 2011) from Agriculture and Food Production

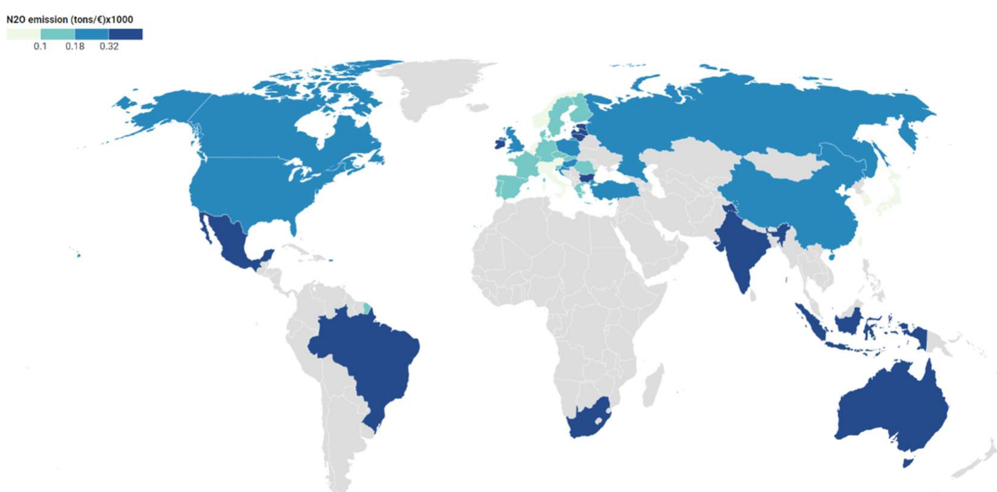
(A) Carbon Dioxide (CO2)



(B) Methane (CH4)

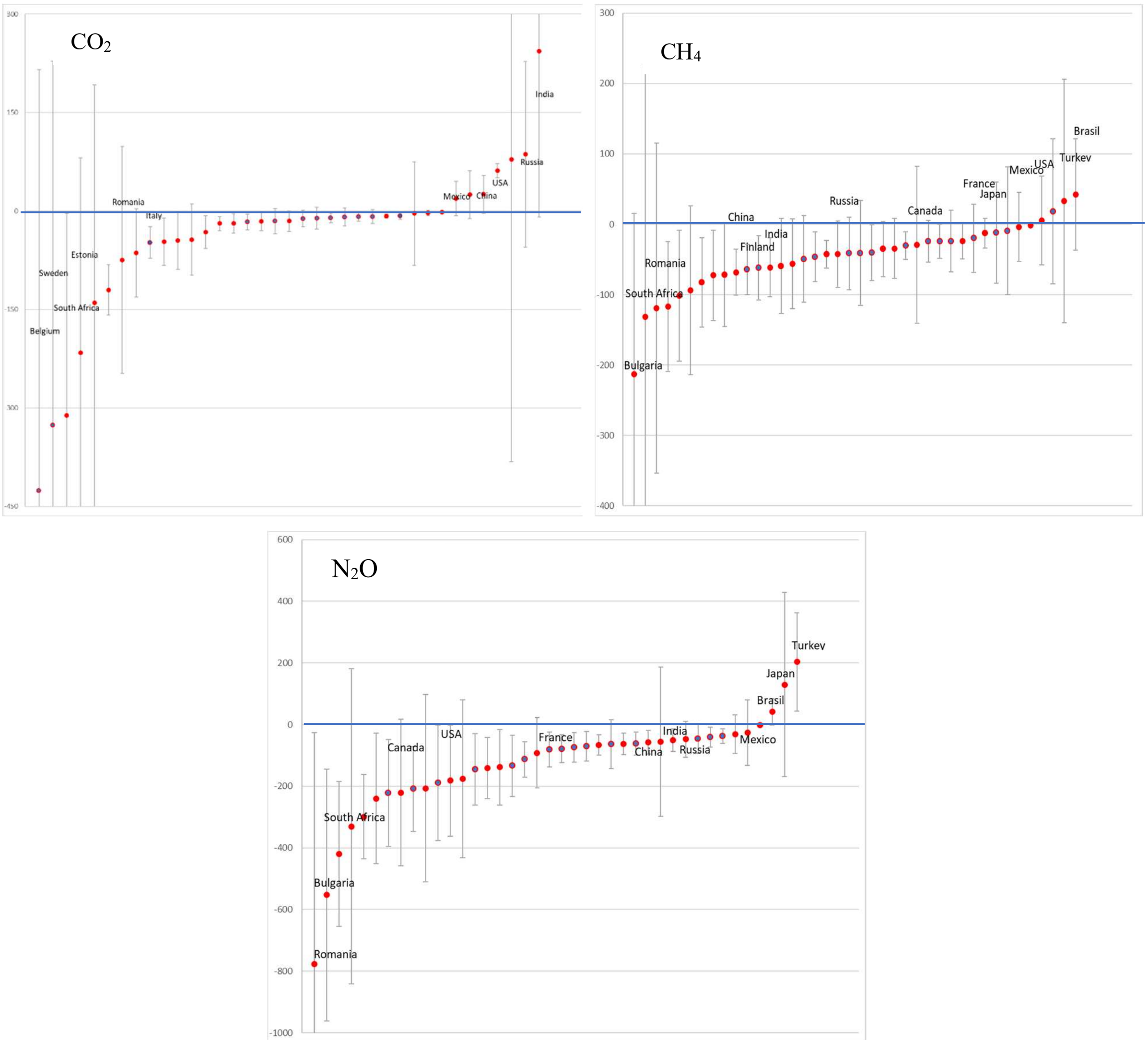


(C) Nitrous Oxide (N2O)



Notes: Emission rates values are expressed as tons of CO2 equivalent per 1000 euro of output, weighted by the value of output.

Figure 2 – Trade Protection and Pollutant Emission Rates (CO_2 equivalent), by Country



Notes: Implicit carbon tax is estimated for 44 (Exiobase) countries from a regression of import tariffs plus ad valorem equivalent of NTMs, on total CO_2 / CH_4 / N_2O emission rate (ton/€). Total emission rate is instrumented with the direct emission rate, measured in the same product but in the ten smallest other countries. A separate regression is run for each country. The observed data come from the years 2001, 2004, 2007, 2010. Red circle are the estimated coefficients (blue dots highlight EU15 countries), vertical bars are robust CI 95 %.

Table 1 – Emission rates of Agricultural and Food products (year 2011)

	Direct Emission Rate (ton/million€)				Total Emission Rate (ton/million€)				Output	Import	AVE
	CO2	CH4	N2O	TOT	CO2	CH4	N2O	TOT	(€ Billions)	Tariff	NTMs
* Food products nec	43	2	3	49	522	215	212	949	1,673	13%	98%
* Products of Vegetable oils and fats	36	13	2	51	463	174	349	986	189	10%	85%
Fish and other fishing products (05)	64	0	0	65	215	50	13	278	244	12%	56%
* Sugar	70	1	4	75	579	214	240	1,034	85	21%	103%
* Meat products nec	67	22	10	98	427	311	147	884	202	19%	57%
Mean of cleanest 5 products	***56***	***8***	***4***	***68***	***441***	***193***	***192***	***826***	***479***	***15%***	***80%***
* Products of meat poultry	58	42	16	117	466	190	315	971	141	28%	31%
Products of forestry, logging (02)	114	8	16	137	263	42	26	331	210	5%	33%
* Products of meat cattle	91	37	16	145	573	3,955	1,897	6,424	142	26%	62%
* Products of meat pigs	64	63	25	152	449	272	309	1,030	117	22%	29%
* Dairy products	131	18	8	157	532	896	279	1,707	320	19%	65%
Animal products nec	96	59	33	188	542	550	156	1,248	67	13%	70%
Crops nec	136	106	120	363	412	198	141	751	244	11%	57%
* Processed rice	392	11	10	413	1,323	2,780	372	4,474	100	17%	119%
Vegetables, fruit, nuts	151	2	328	481	415	56	350	821	561	15%	69%
Poultry	124	8	502	634	525	181	669	1,375	166	9%	38%
Pigs	130	164	506	799	483	341	616	1,439	138	15%	72%
Plant-based fibers	420	15	430	865	1,009	681	489	2,179	50	4%	16%
Sugar cane, sugar beet	356	77	452	885	677	246	523	1,446	49	9%	24%
Oil seeds	286	19	758	1,063	574	172	815	1,561	101	7%	64%
Cereal grains nec	271	71	836	1,179	676	272	894	1,842	187	11%	55%
Wheat	428	6	1,055	1,490	1,124	217	1,141	2,483	114	8%	63%
Meat animals nec	222	1,814	1,728	3,764	622	2,464	1,811	4,897	39	10%	11%
Paddy rice	358	4,060	386	4,804	1,254	5,532	513	7,299	128	17%	103%
Wool, silk-worm cocoons	3,812	2,837	919	7,567	4,221	3,655	980	8,856	5	4%	46%
Cattle	372	5,683	2,686	8,741	703	6,331	3,054	10,088	145	12%	49%
Mean of dirtiest 5 products	***1,038***	***2,880***	***1,355***	***5,273***	***1,585***	***3,640***	***1,500***	***6,725***	***86***	***10%***	***54%***

Notes: Emission rates values are expressed as tons of CO2 equivalent per million euro of output and refer to the mean value across countries, weighted by the value of output. Data come from Exiobase. Tariff data come from CEPII MAcMaps-HS6 database; NTMs, reported as AVEs of NTM, come from Niu et. al (2018) estimation. Average tariff and NTM refer to year 2010.

(*) Food products.

Table 2 – Trade Policies and CO2 emission rates

	PANEL A: Import Tariffs					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
CO2 Emiss	-3.3761***	-9.7755***				
	(0.2652)	(1.0647)				
CH4 Emiss			-0.7359***	-7.7565***		
			(0.2427)	(1.0621)		
N2O Emiss					-4.9229***	-24.8252***
					(0.6050)	(1.8179)
No. of obs.	15,877	15,784	16,032	15,816	15,885	15,771
R-Sq	0.21	0.20	0.20	0.19	0.20	0.16
K-P F statistic		124.1		677.2		462.6

	PANEL B: AVE of Non-Tariffs Measures					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
CO2 Emiss	-1.3476**	-9.9230**				
	(0.5772)	(3.8881)				
CH4 Emiss			-3.0987**	-11.6880***		
			(1.2953)	(2.7015)		
N2O Emiss					-12.3872***	-44.5588***
					(2.6371)	(6.0366)
No. of obs.	6,824	6,758	6,866	6,799	6,804	6,749
R-Sq	0.27	0.27	0.28	0.27	0.28	0.27
K-P F statistic		79.3		428.6		233.9

	PANEL C: Import Tariffs + AVE of Non-Tariffs Measures					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
CO2 Emiss	-5.0376***	-20.2173***				
	(1.4855)	(4.7380)				
CH4 Emiss			-3.9612***	-16.0624***		
			(1.4774)	(4.1425)		
N2O Emiss					-17.8866***	-57.9555***
					(2.9079)	(7.4415)
No. of obs.	6,749	6,707	6,815	6,687	6,751	6,696
R-Sq	0.26	0.25	0.26	0.25	0.26	0.24
K-P F statistic		79.2		632.3		239.2

Notes: CO2, CH4 and N2O emission rates are expressed in CO2 equivalent, measured in metric tons per Euro of output and weighted by the value of imports. Importer tariffs are weighted on the values of "reference groups of countries", AVE of NTMs are weighted on the values of imports. All regressions include country dummies, year dummies and constant, not reported. OLS is ordinary least squares, IV is instrumental variables. The instruments are the direct emission rates measured in the same industry but in the ten smallest other countries. K-P F statistic denotes the Kleibergen-Paap Wald F statistic to test the validity of the instrumental variable. The observed data come from the years 2001, 2004, 2007, 2010. Robust standard errors in parentheses. Asterisks denote p value: * < 0.10, ** < 0.05, *** < 0.01.

APPENDIX

Table A1 – List of countries

Importing countries				
* Afghanistan	* Colombia	* Hungary	Montenegro	Solomon Islands
Angola	Comoros	* Indonesia	Mongolia	Sierra Leone
Albania	* Cabo Verde	* India	Mozambique	* El Salvador
United Arab Em.	* Costa Rica	* Ireland	Mauritania	Serbia
* Argentina	* Cuba	Iran, Islamic Rep.	Montserrat	Suriname
Armenia	* Cyprus	Iceland	* Mauritius	* Slovak Republic
Antigua & Barbuda	* Czech Republic	* Israel	* Malawi	* Slovenia
* Australia	* Germany	* Italy	* Malaysia	* Sweden
* Austria	Djibouti	* Jamaica	Mayotte	Swaziland
Azerbaijan	Dominica	Jordan	Namibia	Seychelles
Burundi	* Denmark	* Japan	* Niger	Syrian Arab Rep.
* Belgium	Dominican Rep.	* Kazakhstan	* Nigeria	Chad
Benin	Algeria	Kenya	* Nicaragua	* Togo
* Burkina Faso	* Ecuador	Kyrgyz Republic	* Netherlands	* Thailand
Bangladesh	* Egypt, Arab Rep.	* Cambodia	Norway	Tajikistan
* Bulgaria	* Spain	Kiribati	* Nepal	Turkmenistan
Bahrain	* Estonia	St. Kitts & Nevis	* New Zealand	Tonga
Bahamas, The	Ethiopia	* Korea, Rep.	Oman	* Trinidad and Tobago
Bosnia and Herzeg.	* Finland	Kuwait	* Pakistan	* Tunisia
Belarus	Fiji	Lao PDR	* Panama	* Turkey
Belize	* France	* Lebanon	* Peru	Tuvalu
Bermuda	Micronesia	Libya	* Philippines	Taiwan, China
* Bolivia	Gabon	St. Lucia	Palau	* Tanzania
* Brazil	* United Kingdom	* Sri Lanka	Papua N.Guinea	Uganda
Barbados	Georgia	Lesotho	* Poland	* Ukraine
* Brunei Darussalam	* Ghana	* Lithuania	* Portugal	* Uruguay
Bhutan	* Guinea	* Luxembourg	* Paraguay	* United States
Botswana	* Gambia, The	* Latvia	Palestine	Uzbekistan
Central African Rep.	Guinea-Bissau	Macao	French Polynesia	St.Vincent& Gren.
* Canada	Equatorial Guinea	* Morocco	Qatar	* Venezuela, RB
Switzerland	* Greece	Moldova	* Romania	* Vietnam
* Chile	Grenada	* Madagascar	* Russian Fed.	Vanuatu
* China	* Guatemala	Maldives	* Rwanda	Yemen, Rep.
* Cote d'Ivoire	Guyana	* Mexico	Saudi Arabia	* South Africa
Cameroon	* Hong Kong	Macedonia, FYR	Serbia and Mont.	Zambia
Dem.Rep.Congo	* Honduras	* Mali	Sudan	Zimbabwe
Congo, Rep.	Croatia	* Malta	* Senegal	
Cook Islands	Haiti	Myanmar	* Singapore	

Notes: All listed countries are used in PANEL A of Table 2 (using importer tariffs); PANEL B and PANEL C include only countries marked by (*) because the use of NTMs data reduces to 94 the number of countries.

Table A2 – First stage IV regression

	Tariffs		
	CO2 Emiss	CH4 Emiss	N2O Emiss
	(1)	(2)	(3)
CO2 Emiss IV	0.5575***		
	(0.0500)		
CH4 Emiss IV		2.6902***	
		(0.1034)	
N2O Emiss IV			1.7571***
			(0.0817)
No. of obs.	15,877	16,032	15,885
K-P F statistic	124	677	463

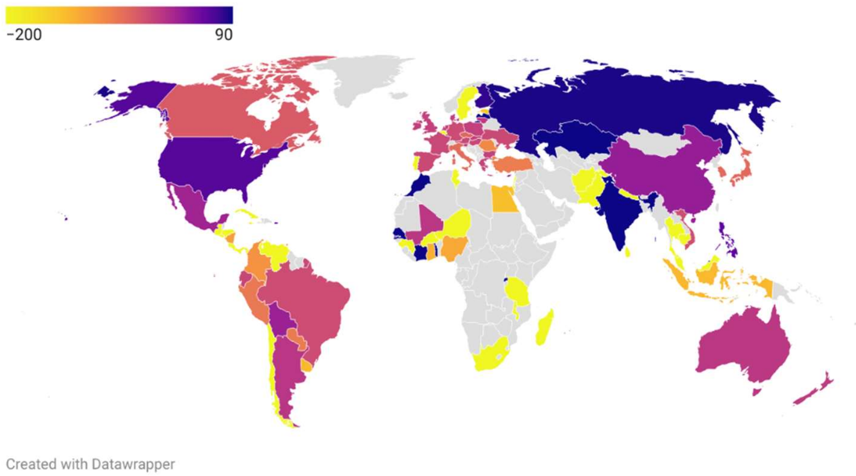
	AVE of Non-Tariffs Measures		
	CO2 Emiss	CH4 Emiss	N2O Emiss
	(1)	(2)	(3)
CO2 Emiss IV	0.5524***		
	(0.0620)		
CH4 Emiss IV		5.1315***	
		(0.2479)	
N2O Emiss IV			1.8332***
			(0.1199)
No. of obs.	6,824	6,866	6,804
K-P F statistic	79	429	234

	Tariffs + AVE of Non-Tariffs Measures		
	CO2 Emiss	CH4 Emiss	N2O Emiss
	(1)	(2)	(3)
CO2 Emiss IV	0.5554***		
	(0.0624)		
CH4 Emiss IV		4.2071***	
		(0.1673)	
N2O Emiss IV			1.8582***
			(0.1201)
No. of obs.	6,749	6,815	6,751
K-P F statistic	79	632	239

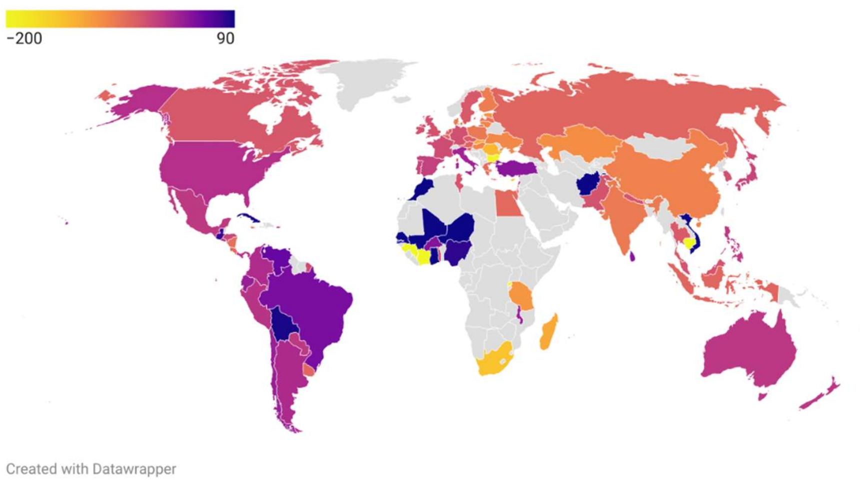
Notes: CO2, CH4 and N2O emission rates are expressed in CO2 equivalent, measured in metric tons per Euro of output and weighted by the value of imports. IV is instrumental variables. The instruments are the direct emission rates measured in the same industry but in the ten smallest other countries. K-P F statistic denotes the Kleibergen-Paap Wald F statistic to test the validity of the instrumental variable. The observed data come from the years 2001, 2004, 2007, 2010. Robust standard errors in parentheses. Asterisks denote p value: * < 0.10, ** < 0.05, *** < 0.01.

Figure A1. Implicit Tax in Trade Policy, by Country

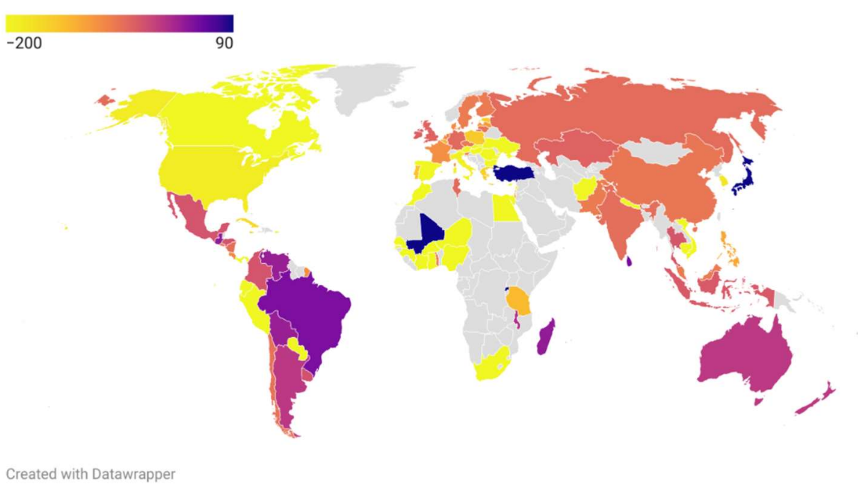
A. Covariance of Trade Protection and CO2 emission rates



B. Covariance of Trade Protection and CH4 Emission Rates



C. Covariance of Trade Protection and N2O Emission Rates



Notes: Implicit carbon tax is estimated for 94 countries from a regression of import tariffs plus AVE of NTMs, on total CO_2 / CH_4 / N_2O emission rate (ton/€). Total emission rate is instrumented with the direct emission rate, measured in the same product but in the ten smallest other countries. A separate regression is run for each country. The observed data come from the years 2001, 2004, 2007, 2010.