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INTERNSHIP REPORT
« Perspectives on a cap and share to end climate change and extreme poverty »

June 25, 2025

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Declaration of Academic Integrity

Hereby I, Marius Le Hénaff, confirm that:

1. The results presented in this report are my own work.
2. I am the author of this report
3. I have not used the work of others without clearly acknowledging it, and quotations and paraphrases from any source are clearly indicated.

June 25, 2025

General presentation

This ongoing internship at CIRED, under the supervision of Dr. Adrien Fabre, has provided a valuable opportunity to gain knowledge, skills, and critical perspective on economics and various other subjects in a cutting-edge interdisciplinary scientific environment.

The research project, led by Dr. Fabre and entitled “Perspectives on a Cap and Share to End Climate Change and Extreme Poverty”, addresses a wide range of scientific and political issues, from the design of international climate policies to the study of global public support for redistribution and decarbonisation[29] [30]. A central component of this research is the evaluation of the feasibility and desirability of a global Cap and Share mechanism, which would impose a binding global cap on fossil CO_2 emissions, distribute emission rights equally across all individuals worldwide, and allow international trading of these allowances. This approach aligns environmental effectiveness with distributive justice and global fairness.[31]

My contributions to the project have focused on two complementary aspects.

I worked on the econometric forecasting of CO_2 emissions, with a focus on consumption-based emissions, which better reflect the carbon footprint of a country’s consumption rather than its domestic production. To that end, I developed several panel data regression models to assess the role of macroeconomic variables—such as GDP, fossil fuel dependence, and trade balances—in shaping national carbon footprints. The aim of this work was not only to evaluate the predictive power of these variables, but also to produce realistic future emissions trajectories that could serve as a baseline for global climate policy assessment. This work is the subject of the written report below.

Second, I contributed to the improvement of the NICE (Nested Inequality Climate Economy) model [1], a DICE-like integrated assessment model [6] that is disaggregated at the country level and structured by income deciles. This structure makes NICE particularly well-suited for evaluating global carbon policies with redistributive impacts, such as a cap and share system or an equal per capita dividend from carbon revenues. My work on NICE included implementing new modelling features—such as the ability to simulate coalitions of countries engaging in joint climate policies—and improving the accuracy and plausibility of key economic inputs, particularly through the integration of the econometric forecasts of consumption-based emissions. These enhancements aim to provide country-level decision makers with clearer and more credible information to support collective climate action.

Abstract

This study overlooks the impact of persistent emission transfers of fossil CO2 through international trade. This study estimates and compares a variety of panel data regressions, including Common Correlated Effects Mean Group (CCEMG) and Mean Group estimators, to assess the role of macroeconomic variables in shaping consumption-based emissions. The study concludes that accurate long-term forecasting of consumption-based emissions requires incorporating persistent structural imbalances in trade and emissions, and that fixed-effect models perform better than gross domestic products in predicting emissions imbalances.

Introduction

In the framework of refining the Nested Inequality Climate Economy (NICE) model [1], this work focuses on improving the representation of international taxes and transfers, in particular the emissions on which countries would effectively pay carbon taxes. In order to represent most precisely the taxes and transfers between and within countries themselves, let us present the distinction between two types of accounting emissions for countries: territory-based emissions and consumption-based emissions. While territory-based emissions reflect carbon emitted within a country's borders, consumption-based emissions account for the carbon footprint of domestic consumption, both in goods and services, regardless of where emissions are produced along global value chains [2].

Up to now in the NICE model, trajectories for territory-based emissions are provided and are used to base the transfers induced by carbon pricing. Yet, in their consumptions, in the case of an international coalition putting in place a carbon price, individuals would pay for the carbon footprint of their consumption of goods and services. The emissions from the production of traded goods and services have increased from 4.3 Gt CO_2 in 1990 (20% of global emissions) to 7.8 Gt CO_2 in 2008 (26%). [3] Since, they have remained relatively stable. [4] Therefore, reporting consumption-based emissions instead of territory-based emissions is a central task to achieve in order to refine the NICE model.

In order to graphically motivate this work, Figure 1. below represents the imbalance of emissions per country in 2022, which is the last year for which the Global Carbon Project provides data. In the rest of the work, these emissions will be called “transfer emissions”. Transfer emissions are positive when consumption-based emissions are higher than territory-based emissions, i.e. when a country is a net importer of emissions.

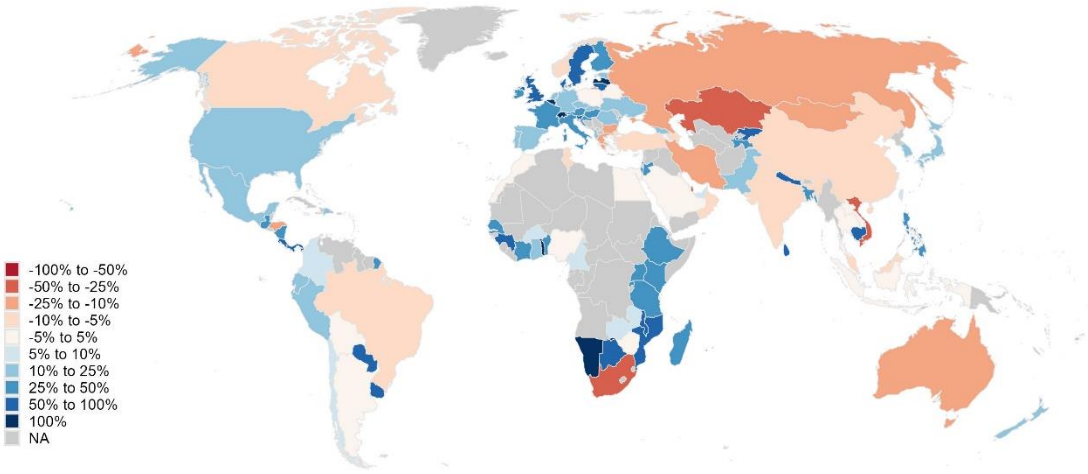

Figure 1: Transfer emissions (% of territory-based) per country in 2022

Indeed, though the global amount of emissions, as well as the total taxes raised by the international carbon price remain the same in both accounting methods, the unaccounted transfer emissions hide significant transfers which would be induced by the equal per capita redistribution of revenue, and therefore omit significant changes in development levels in the poorer countries.

The objective of this work is to develop a forecasting method for country-level consumption-based emissions using observable macroeconomic variables for which long-term projections already exist or can be modelled. In particular, one could think that trade balances would be variables of interest in modelling consumption-based emissions. In NICE, emissions trajectories come from the model REMIND[5], which assumes that trade balances converge towards zero by 2050. In addition, according to trajectories of emissions from the DICE-2023 model [6], to which the NICE model is close, countries would still emit CO2 by 2070. This statement would remain true event under a scenario which would lead to a temperature increase below 2°C above preindustrial levels.

In this context, it is important to consider the question asking whether the method used to model trade balances matters in order to model the most accurately emissions.

Indeed, emissions transfer are determined by the amount of goods and services that are traded between countries, and their carbon intensity determine the amount of transfer emissions. Hence, one could think that modelling consumption-based emissions using the hypothesis that trade balances globally converge to zero would be a significant issue. Answering this question is an aim of this work, and the question will be central to this work.

The aim of this study is to identify statistically significant relationships between consumption-based emissions and relevant economic variables — including GDP, fossil fuel dependence, and trade balances — that can be used for long-term forecasting. Depending on the different contexts and the available data in which consumption-based emissions need to be modelled, this work tries to model consumption-based emissions using a distribution of territory-based emissions or not, and several economic variables, in particular GDP and different types of balances, which happen to be the most significant variables as well as the ones which are the most commonly modelled.

The main results that are found in this study are the following:

- **Trade balances significantly explain consumption-based emissions and transfer emissions and are helpful to model them**, but it is not the case for territory-based emissions. Therefore, assuming that trade balances converge toward zero by 2050 is acceptable for long-term models using territory-based accountability, but not for long-term models that use consumption-based accountability.

- **Trade balances of fuels can explain significantly consumption-based emissions for some countries** and contribute to modelling them accurately, but not for all of them.

- The marginal effect of GDP on consumption-based emissions is not significant. In addition, **when it comes to modelling transfer emissions, a fixed effect is more accurate than including GDP in the independent variables**.

Literature review

Territory-based emissions and consumption-based emissions of carbon dioxide, and their nexus with other economic variables, are subjects that are widely discussed in the literature and for which there are already thousands of articles approaching the subject from different angles. At the nation-wide scale, there are many papers that offer statistical analyses of consumption-based emissions or territory-based emissions. There are also for groups of countries. In this literature review, let us present the articles which have been significant in orienting this work, defining the methods and framing the problem. This is not a systematic literature review, and it is not meant to be exhaustive, yet it is useful to place this study in a working context.

Davis and Caldeira (2010)[2] introduce one of the foundational contributions to consumption-based emissions accounting by directly comparing production-based and consumption-based measures of CO_2 emissions. They illustrate how international trade causes significant emission transfers between countries, often shifting emissions from developed to developing economies. Their work strongly motivates the need for models that explicitly incorporate consumption-based perspectives when designing international climate policy or simulating redistribution mechanisms, as is the case in the present work aiming to improve IAMs like NICE.

Liddle (2018) [7] runs an econometric analysis of the significance of various economic variables on a database gathered by the Global Carbon project [3][8][9], which we will further use in our analysis. Their method uses cross-correlated effects mean group (CCEMG) regressions [10], from which the method of this work strongly inspires because it allows to account for the non-stationarity, the heterogeneity and the cross-dependence of the time series that we use.

The main facts that they draw from their analysis are the following. Trade is significant for consumption-based emissions but not for territory-based emissions, which strengthens the interest for how to model transfer emissions though trade balances are complicated to forecast. By highlighting the significance of trade balances, GDP per capita, prices of fuels, as well as the share of fossil fuels in the economy, it gives many variables which could be useful in the forecast of consumption-based emissions. Yet it does not tackle this particular question of the predicting power of such variables, which highlights the importance of this work.

This article leads us to think about the following statement, which drives this study: econometric estimations require in their assumptions that the estimated model be the real one. In our case, the true model is a model which reflects the accountability identity: transfer emissions equal balances in volume of goods and services times the carbon-intensity of each product that is traded. Yet because trade balances for each product are profoundly uncertain and depend on multiple variables that determine them in the future, our analysis will only be partial.

Also, since the time span of the database only covers thirty years, the time series which are reported yearly are not long enough to capture the impact of the variation of each data. Indeed, with only four independent variables, and their cross-sectional variables, which are included due to the CCEMG methodology, the R-squares of their regressions are extremely high. Yet, the predicting power can be expected to be lower because of overfitting. Consequently, the choice of the regressors is crucial and it would reflect the relationship that the study highlights. The work is less about predicting exact trajectories of transfer emissions or consumption-based emissions for the future, but rather about highlighting scenarios that the available data allows to model, understanding which variables and relations are chosen to drive the determination of emissions, and what reality they represent.

Other articles provide insightful information for this case. Peters et al. (2011)[3] document the increasing role of international trade in global carbon emissions. Between 1990 and 2008, emissions embodied in traded goods rose from 4.3 Gt CO2 (20% of global emissions) to 7.8 Gt CO2 (26%). This transfer of emissions through trade reflects the redistribution of carbon footprints from production to consumption, particularly from developing to developed countries.

Similarly, Mahlkow and Wanner (2023)[11] demonstrate that persistent global trade imbalances are associated with higher global emissions. Their study is particularly interesting for this work for the stylized facts that they establish in the first part of their article, and which reports static behaviours across time which would be relevant to capture, and which could take a significant part in the modelling of emissions imbalances. The fact that both the trade balances and the emissions balances persist over time could be a way to capture for the diversity of behaviours across countries, and could provide fixed effects that would be modified by added marginal effects afterwards. Another interesting stylized fact is that many large fossil fuel exporters are consistently running strong trade surpluses. The last one in our scope of interest is that countries with large value deficits (respectively surpluses) tend to import more (respectively less) emission-intensive products than they export. These stylized facts are strong arguments to analyse and search for persistent effects in the emissions patterns of countries.

Let us illustrate these stylized facts with data used in this study.

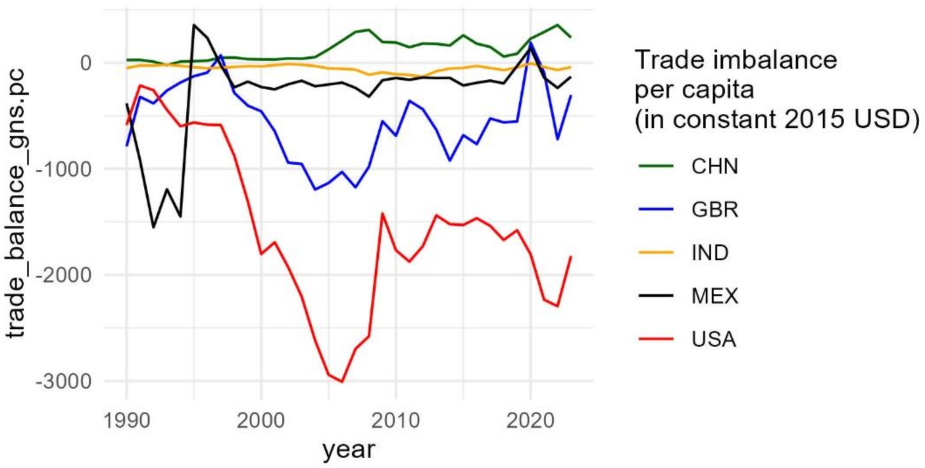

Figure 2: Transfer emissions of CO2 by year between 1990 and 2022

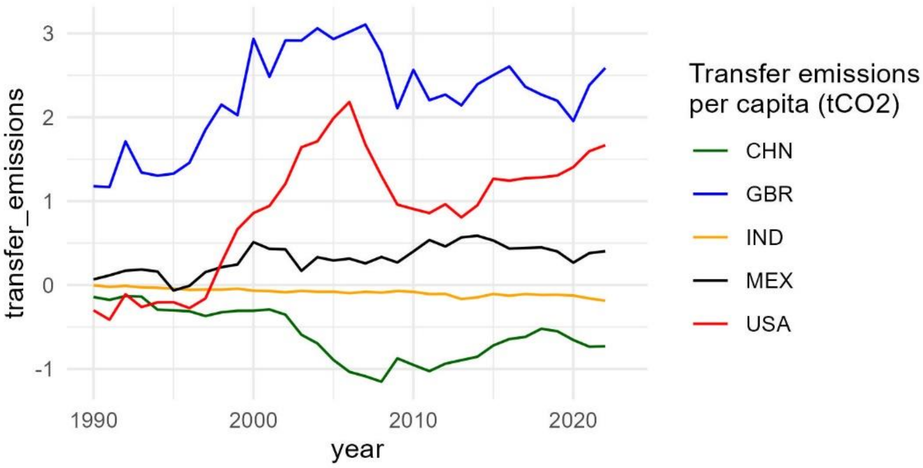

Figure 3: Trade imbalances by year between 1990 and 2022

Indeed, Figure 2 and Figure 3 show persistence through time in both trade imbalances and in CO2 emissions embodied in trade.

Knight and Schor (2014) [12] focus on the relationship between economic growth and emissions in high-income countries. Analysing 29 developed nations from 1991 to 2008, they find that GDP growth tends to increase consumption-based emissions more strongly than territorial emissions. They observe that while some degree of relative decoupling (slower growth of emissions relative to GDP) occurs for territorial emissions, no such decoupling is observed for consumption-based emissions. This observation echoes the findings of Haberl et al. (2020) [13], who conduct a comprehensive review of the global decoupling literature. They conclude that although relative decoupling of GDP and CO2 emissions is common, absolute decoupling (where emissions decline despite economic growth) remains rare, especially when consumption-based emissions are considered.

Focusing on developing economies, Wang et al. (2024) [14] examine the decoupling dynamics in 55 African countries. Using a newly compiled MRIO database, they find that only 14 countries have achieved absolute decoupling of consumption-based emissions from GDP growth. They also analyse the role of industrialization and trade openness on consumption-based emissions in sub-Saharan Africa, finding that both factors significantly contribute to higher carbon footprints.

The methodological approaches used to model and forecast emissions are also diverse. In addition to CCEMG estimators, some studies employ convergence analysis. For example, Bhattacharya et al. (2020) [15] apply club convergence methods to analyze both territorial and consumption-based carbon intensities across 70 countries. They find that countries are converging into distinct carbon intensity "clubs," with the number of high-intensity consumption clubs projected to increase in the coming decades, potentially complicating international cooperation on climate targets.

More recently, machine learning approaches have been introduced to improve the accuracy and interpretability of forecasts. Aras and Van (2022) [16] propose an interpretable forecasting framework that relies on machine learning models to decompose the contributions of different predictors to CO2 emissions forecasts in Turkey. While the results are very high, the predictions are mainly short-term and focus only on one country, which does not fit the purpose of this work.

Pollitt and Alexandri (2019) [17] analyse global carbon leakage and consumption-based emissions using multi-regional input-output (MRIO) models. Their work illustrates the importance of modeling embodied emissions transfers through international trade, highlighting how differences in national carbon intensities and trade flows shape consumption-based emissions profiles. They compare projections using three methods of accountability: production-based accounting, consumption-based accounting, and technology-adjusted consumption-based accounting of emissions. When accounting for exports, the third method compares the carbon-intensity of a product to the global average carbon-intensity, arguing that a unit produced well below the average contributes to the decarbonisation of the global economy by substituting to other products. Though this method does not interest us for the current work, it could be relevant in later design of international climate policies, because it fits the "best in class" approach that is used in Europe Union.

Then, a result of this study that happens to be very relevant to this work is that their projections forecast that China would become a net importer of emissions in consumption-based accounting by 2020. Though it has not happened yet in the data, it is arguable that the strong decarbonation of Chinese territorial emissions would make this assumption plausible. Therefore, in the current work, the attention should be drawn to the differentiated decarbonation of national territorial emissions, in a consumption-based approach, and interest in how this could be significant in the projections.

Constantini et al. (2024) [18] explore the possibilities of forecast using techniques of machine learning, in particular random forest regressions and multiplicative regressions. Their approach incorporates a wide range of predictive variables, including GDP, advanced well-being indicators, and indices of R&D investment in the green economy. They achieve robust results, demonstrating high predictive accuracy up to 15 years ahead. While this work is highly relevant to the present study in its forecasting ambition, it also highlights a key limitation for integrated assessment modeling: the complexity and low predictability of many of the input variables (e.g. Economic Complexity Index, the economic Fitness, and the Generalized Economic Complexity idex). For long-term scenarios, particularly those generated by IAMs like NICE, predicting such indicators may be as demanding as directly modeling trade balances and the carbon intensities of traded goods—the very complexities this work seeks to circumvent.

Esso and Keho (2016)[19] explore the dynamic relationship between energy consumption, economic growth, and carbon emissions in selected African countries using cointegration and causality tests. Their results suggest strong bidirectional causality between economic growth and emissions, and highlight the importance of energy consumption as a driver of emissions in developing contexts. While the regional focus is narrower, these findings emphasize that the economic development pathway—captured by GDP growth and energy intensity—plays a crucial role in shaping consumption-based emissions, and should therefore be carefully modeled when designing long-term scenarios.

Wang (2024) [20] analyzes the role of industrialization on consumption-based emissions in sub-Saharan Africa in the context of achieving the Sustainable Development Goals. The study shows how industrialization pathways contribute significantly to variations in consumption-based emissions across developing economies. This work supports the need for differentiated modeling approaches depending on regional characteristics and levels of development. It reinforces the argument that the structural composition of economies—particularly the industrial sector—must be carefully considered in forecasting consumption-based emissions.

Halicioglu (2009) [21] presents an econometric study focused on Turkey, investigating the relationships between CO_2 emissions, energy consumption, income, and foreign trade. Using cointegration and error correction modeling, the paper confirms the existence of long-run relationships between these variables, and finds that both energy consumption and foreign trade significantly drive CO_2 emissions. While the study is limited to a single country, it highlights the crucial role of trade balances and foreign trade in driving emissions, which resonates with the present work's focus on transfer emissions and consumption-based emissions. The cointegration methodology also offers useful insights for handling non-stationary time series data.

Data and methodology

The emissions data utilized in this analysis are sourced from the Global Carbon Atlas (Peters et al., 2011 [3]; Friedlingstein et al., 2020 [8]; Andrew and Peters, 2023[9]), which provides both territory-based and consumption-based emissions data for each country. Territory-based emissions represent the CO_2 released within a country's borders, whereas consumption-based emissions account for the emissions associated with the goods and services consumed by residents, including emissions from imports and excluding those from exports. This data covers the period from 1990 to 2022.

There is a discrepancy between the global emissions reported by the Global Carbon Atlas and the computed sum of country-level emissions, which is derived using WDI population data and Global Carbon Atlas data for per capita emissions. For instance, in 2020, the sum of national consumption-based emissions deviated from the global total reported by the Global Carbon Atlas by approximately 526 $MtCO_2$. Of this discrepancy, 246 $MtCO_2$ can be attributed to countries not included in the NICE model, such as Venezuela, Somalia, New Caledonia, and Trinidad and Tobago, for which data from the World Development Indicators [22] database was unavailable. Additionally, Taiwan, for which there are no data in the World Bank database, could not be included in the analysed dataset. The missing data for Taiwan explain the last missing 280 MtCO2.

This discrepancy is considered acceptable within the current context but is noted as a source of un-certainty, which could potentially be mitigated with more harmonized data in future studies. For now, the lack of precision in accounting of total fossil CO2 emissions allows a margin of error for the estimate of the total balance of the estimates. It is a clear limitation to the study and will be discussed later.

The Global Carbon Project database provides data on land use, land use change, and forestry. Although emissions in the NICE model and the MIMIFAIR module include this category, the Global Carbon Project data are not presented in a consumption-based accounting format. The treatment of land use data has not been addressed in this work up to this point. Several possibilities exist for incorporating land use data, but they would require further exploration and discussion. Land use emissions could be added to projections of consumption-based emissions, or they could undergo the same transformation process to convert territory-based emissions into consumption-based emissions using the prediction estimates.

Macroeconomic and energy data were sourced from the World Bank's World Development Indicators (WDI) database. The variables utilized include GDP at purchasing power parity (PPP, constant 2021 USD), fossil fuel energy consumption as a percentage of total energy use, industry value added as a percentage of GDP, exports and imports of goods and services as a share of GDP, net fuel energy imports as percentage of total energy use , and population data. Population data were used for per capita transformations and for constructing population-weighted global averages. GDP data were transformed into logarithmic form and expressed on a per capita basis. More detail about the variables used is given at the end of Annex A.

Let us now present the methodology for developing a prediction method for these data.

Building on previous work involving similar databases (e.g., Shahbaz et al., 2017 [23]; Liddle, 2015 [24]), as well as research conducted on the same dataset spanning only from 1990 to 2008 (e.g., Liddle, 2018 [7]), it is acknowledged that the data exhibits cross-national dependence and non-stationarity. These characteristics can be formally assessed later through the use of Pesaran (2004)[26] cross-sectional dependence tests and Pesaran (2007) [25] panel unit root tests designed for datasets exhibiting cross-sectional dependence. It has not been done yet but it is possible to test on this updated set of data.

The primary objective of this work is to provide trajectories for consumption-based emissions that can be effectively modelled. To achieve this, we employ the following regression techniques:

Cross-correlated effects mean group estimates, initially introduced by Pesaran (2006) [10] and previously utilized by Liddle (2018) [7], are employed due to their capability to test the significance of parameters. These regressions are particularly useful as they account for cross-sectional dependence, heterogeneity, and non-stationarity by incorporating cross-sectional means of both dependent and independent variables as independent variables. This approach helps identify which parameters are significant and provides insights into which variables and combinations may be suitable for predicting variables in subsequent phases.

The form of CCEMG regressions would be the following, when using logged GDP per capita and the share of fossil fuel in total energy use as independent variables to estimate a specific type of emissions:

$$emissions_{it} = \alpha_i * \log(GDP_{it}) + \beta_i * fossilfuelshare_{it} + Z_{it} + A_i + u_{it} \quad (1)$$

In this case, αs and βs are cross-sectional specific coefficients to be estimated, A is a cross-sectional specific constant, u is the error term, and Z represents the cross-sectional average terms. Those cross-sectional average terms are represented in equation (2) below:

$$Z_{it} = b_i * \overline{emissions_{it}} + c_i * \overline{\log(GDP_{it})} + d_i * \overline{fossilfuelshare_{it}} \quad (2)$$

However, this method is complemented by mean group regressions. For instance, when one tries to estimate consumption-based emissions using territory-based emissions as an independent variable, applying strict CCEMG regressions would involve including the average of global emissions twice, as territorial emissions and consumption emissions average to the same global quantity. This redundancy also applies to trade balances, as well as the average of the ratio of consumption based-emissions over territory-based missions, which inherently sum to zero and one respectively, and exports and imports, which should theoretically balance. Including these artificial averages might not capture variations that carry economic meaning and predictive power and could introduce severe collinearity issues, thereby distorting the results.

To address these problems and derive suitable formulas for prediction, we employ Mean Group Estimators (Pesaran and Smith, 1995) [27], to which are incorporated global averages in order to capture cross-national trends. This approach could be more sensible for capturing global tendencies in emissions. Mean group regressions involve estimating OLS coefficients for each country and then averaging these coefficients across countries for each independent variable.

To compare the fitness of these regressions, we implement Pesaran (2004) [26] cross-sectional dependence tests on the residuals, as well as tests for serial correlation.

The dataset is divided into two parts: the period from 1990 to 2010 is used to establish regression coefficients, while the period from 2011 to 2020 is allocated for predictions. The Mean Group (MG) regressions yield tables of linear coefficients for each regression, which are subsequently used to forecast emissions, typically over the period from 2016 to 2020. This time frame corresponds to a forecast horizon of five to ten years. Note that in some instances, to increase the amount of data available for training and validation sets, the regression stops in 2009, and the predictions span from 2015 to 2019.

Once the predictions are generated, all errors are converted into consistent units. They are measured in metric tons of CO2 per capita and as a percentage of the annual consumption-based emissions. For each regression, a mean absolute error is calculated over the five-year prediction evaluation period. This error is then expressed as a percentage of the country's consumption-based emissions in the year 2020.

The evaluation metric for the entire regression is the mean absolute error over the five years of prediction, which corresponds to the average of the national mean absolute errors over the five years, weighted by the territorial emissions per country (not per capita) in the year 2020.

Additionally, the balance of predictions is assessed. For the final year of the predictions, the predicted consumption-based emissions are summed, and the percentage of imbalance is computed. It is important to note that over the 113 countries for which there are consumption-based emissions time series, the sample covers 93.1% of global emissions (32.7 Gt out of 35.1 Gt). The sample is almost perfectly balanced regarding the aggregate sums of emissions. There is a deficit of 48 Mt CO2, where consumption-based emissions are less than territory-based emissions, representing 0.15% of the total sum of emissions.

Several possibilities are explored: by combining the results of multiple regression formulas deemed acceptable for projecting emissions, different regressions can be merged to obtain the optimal regression for each country. This approach aids in modelling outliers and results in a table that can subsequently be implemented in various models to statistically estimate consumption-based emissions.

Once the analysis is completed for the 113 countries with available consumption-based emissions data, we proceed to match the remaining 66 countries. Using the division into 20 regions from the World Population Prospects and GDP data from the World Development Indicators database, each missing country is matched with the country having the closest GDP per capita within its region. This matching process extends coverage to all countries except those for which GDP data are unavailable, specifically Yemen, Taiwan, French Polynesia, Eritrea, and Cuba. For these low-emitting countries, consumption-based emissions are assumed to be equal to territory-based emissions.

Employing the same methodology, we also test a regression attempting to assess a fixed effect for each country and a quadratic effect of GDP on the ratio of consumption-based emissions to territory-based emissions for each country. The coefficients are estimated using first differences to capture the dynamic effects.

Results

Out of the 38 regressions completed with Mean Groups Estimators, 17 study the ratio of consumption-based emissions over territory-based emissions, 7 study the logged form of consumption-based emissions, 6 of them the transfer emissions, 2 of them the consumption-based emissions, 4 of them the territory-based emissions, 1 of the logged form of territorial emissions, and 1 of them another variable. 33 variables are used as independent variables. The full summary of the regressions completed can be accessed in Annex A. Let us proceed to the highlight of the main results that can be drawn from this.

As a landmark for comparing the fitness of regressions, let us remind all the indicators that are available in this work:

- The significance of the independent variables used to estimate consumption emissions
- R-squared of the regression, which is often larger than 0.95 for regressions with more than 5 regressors.
- The p-value of the test of cross-sectional dependence on the residuals, which assesses whether the chosen form of the regression captures the cross-national trends.
- The mean absolute error of the predictions, both on the tenth year after the last year of training, and averaged per country between the fifth year and the tenth year after the end of training.
- The difference between the sum of predicted consumption emissions and the actual sum of consumption emissions after ten years of training.

The landmark regression used to compare the effect of other regressors is the fixed ratio: the mean fixed ratio of consumption-based emissions over territory-based emissions is taken for each country over the training set, and used on the validation set. The results for this baseline regression are the following:

The mean absolute error over the last 5 years of prediction is 308 kgCO2 per capita, which amounts to 6.9% of the global average of emissions per capita in 2020 (4.47 tCO2). This method underestimates the total sum of emissions by 960 MtCO2, which amounts to 2.93% of the total of consumption emissions over the sample of countries considered in 2020. One would expect that an estimate method that can be deemed acceptable in order to model consumption-base emissions on the long-term scale would at least increase the performance of these indicators.

To present the results of this research, let us start with the reproduction of the regression completed in Liddle (2018)[7] on the extended dataset. Table 1 presents the results of two regressions reproduced. As in the article, GDP and fossil fuel share are significant for both territory-based emissions and consumption-based emissions. Trade only is significant for consumption-based emissions. Yet, the order of magnitude of the marginal effect of the share of fossil fuel in the energy mix is lower by one order in this estimate. However, when it comes to the predictive power of this formula, the mean absolute error (MEA) is 4.83tCO2 per capita ten years after the last training year, when it comes to modelling consumption-based emissions, and 1.08tCO2 per capita for territory-based emissions. One might argue that these two particular regressions differ from the fixed ratio estimate because they do not assume a distribution of territory-based emissions over the predicted periods. Yet, one might also argue that predicting emissions with an absolute margin of error of 25% is not acceptable, at least without further investigation.

Table 1: Trade and carbon emissions. Panel data spans 1997-2020.

Dependent variable:	Territorial emissions	Consumption emissions
GDP (log p.c.)	0.573^{***}	0.645^{***}
	(0.085)	(0.185)
Fossil fuel share	0.026^{***}	0.020^{***}
	(0.002)	(0.003)
Industry share	0.002	0.002
	(0.002)	(0.003)
Imports G&S (%GDP)	0.0005	0.005^{***}
	(0.001)	(0.002)
Exports G&S (%GDP)	0.001	-0.006^{***}
	(0.001)	(0.002)
Observations	2,712	2,280
R^2	0.999	0.996
Note :	*p<0.1, **p<0.5, ***p<0.01	

From the various CCEMG regressions that have been tested at first, the following conclusions can be drawn. There are several trade-offs to take into account when deciding which independent variables to include in a regression:

- First of all, note that there only are about fifteen training periods per country in the dataset, and, in a CCEMG estimate, one independent variable is added with its cross-national average, which adds twice as much variables as in a regular OLS estimate. Due to this, adding independent variables increases the ability to capture cross-national trends and country-specific effects, but, there is an increased risk of overfitting the values. It is clearly the case in the regression using the Liddle (2018)[7] regression.

- In addition, one must be careful to the difference between the significance of the parameter in its ability to explain variation in emissions data and the fitness of this variable to predict emissions. The causality there is very important. One might notice that it is particularly the case for GDP and the share of fossil fuel. This will de deepened afterwards when examining the Mean Groups regression.

Let us now focus on the analysis of the Mean Groups regressions. The detailed results of the regressions are synthesized in Annex A.

Over all the variables tested for their predictive power, the following are most worthy of attention.

Regression 2 is typical of the kind of results that are obtained in the sample of regressions tested. We are testing predictions using significant variables, which are logged forms of GDP, exports and imports of G&S, and territorial emissions, which could be coherent when considering an identity of the form below,

$$consumption_{it} = territorial_{it} * (1 - emissions\_exports\%_{it} + emission\_imports\%_{it})$$

Indeed, the mean absolute error is close to that of the fixed ratio, the CD p-value is of the order of magnitude of 1e-10, which means that the regression leaves cross-national trends aside. Only the balance of emissions reaches -0.1%. In comparison with the results obtained with other regressions, regression 2 seems pretty satisfying, yet one could doubt that it would be acceptable to include in an IAM without further investigation. Table 2 below presents the results of this regression.

Similarly, in regression 25, the same idea is tested, but this time without putting variables in logged form. The conclusions are similar. The CD statistic cannot exclude the cross-sectional dependence hypothesis. The balance of emissions is -5.2%, and the mean absolute error over five years is 0.98 tCO_2 per capita per year.

One would now want to know if reducing the number of dependent variables could avoid overfitting, and could allow for a better predictive power. In order to illustrate this point, let Table 3 and Table 4 display the results of four relevant Means Groups regressions.

One would like to say that regressions 10, 11, and 17 for example reach mean absolute errors in their predictions that are as good as those of the fixed ratio estimate (510 $kgCO_2$ per capita). From there, it could be arguable that merging the estimates of these four models (regressions 10, 11, 17 and the fixed ratio estimate) by taking the best regression for each country. Yet two arguments seem to strongly reject this possibility:

- Firstly, the CD p-value can be said equal to zero for regression 10, 11, 17. This means again that the model misses cross-national tendencies.

- The significance of independent variables across regressions lacks coherence, which means that most regressions are too far from the true model. Also, reducing the number of independent variables in order to have better predictions (see in particular regression 11 and regression 12) clearly highlights the counterpart which is a high omitted-variable bias.

For these reasons, a result of this analysis is that the statistical prediction of consumption-based emissions using macroeconomic variables and a distribution of territory-based emissions is not conclusive for the moment.

The best prediction that can be done for now is the following:

One can notice that the regressions 10, 11, 17, and 20 are the regressions with the lowest mean absolute error over five years, as well as error of total predicted emissions which range within 2% of the balanced state. However, it is clear that those regressions leave cross-national trends uncaptured, and that there miss significant variables to accurately predict consumption-based emissions.

Then, the matching methodology described earlier to assess a prediction formula to each country. First of all, for countries for which there is at least one estimate available, the one which provides the lowest MEA is assessed, among the fixed ratio, and regressions 10, 11, 17, and 20. Afterwards, for the countries left, the country with the closest GDP per capita in the same region (according to the WPP split of countries) provides its regression coefficients as the ones used for the concerned country. Annex B presents the results of this methodology and the share of countries between each regression.

Table 2 : Regression 2 and regression 25

Dependent variable	log_consumption	consumption_emissions
	Regression 2	Regression 25
log_emissions_pc.world	0.142	
	(0.296)	
log_territorial	0.714***	
	(0.064)	
log_gdp	0.183	
	(0.150)	
log_gdp.world	-0.211	
	(0.142)	
log_imports_gns_percent	0.259***	
	(0.075)	
log_exports_gns_percent.world	0.228*	
	(0.135)	
log_exports_gns_percent	-0.341***	
	(0.077)	
territorial_emissions		0.825***
		(0.127)
gdp		0.0001**
		(0.0001)
emissions_pc.world		0.943
		(0.645)
trade_balance_gns		-0.000
		(0.000)
trade_balance_goods		-0.000
		(0.000)
gdp.world		-0.0002**
		(0.0001)
Constant		-0.450
		(2.471)
Observations	1,782	1,350
CD	1.64 e-10	1.80 e-4
R^2	0.994	0.984
Note:	*p <0.1, **p<0.05, ***p<0.01	

Table 3 : Results of regression 10, 11, 12 and 17

Dependent variable :	emissions_balance_percent			
	(10)	(11)	(12)	(17)
balance_fuel_percent_gdp				-4.655***
				(1.131)
trade_balance_gns_percent	-0.224			-0.497
	(0.351)			(0.415)
exports_gns_percent		-0.331	-1.151***	
		(0.332)	(0.313)	
imports_gns_percent		0.576*	1.098***	
		(0.314)	(0.296)	
fuel_imports_percent_gdp			16.287	
			(14.561)	
fuel_exports_percent_gdp			10.239	
			(10.047)	
exports_gns_percent.world			0.916**	
			(0.407)	
Constant	23.920***	3.122		
	(6.023)	(10.634)		
Country fixed effect	Yes	Yes	No	No
Observations	1,386	1,386	801	910
R^2	0.831	0.891	0.998	0.853
CD test	0	0	0.89	1.12 e-5
Note:	*p<0.1, **p<0.05, ***p<0.01			

Table 4 : Statistics on regressions 10, 11, 12, 17 and their predictions

	Regression 10	Regression 11	Regression 12	Regression 17
R-square	0.831	0.891	0.998	0.853
CD test	0	0	0.889	1.12 e-05
MAE	0.259	0.284	0.794	0.288
Balance percent	2.28	2.30	-1.66	2.71

An interesting conclusion is that **the trade balance of fuel per country helps having better predictions of transfer emissions for some countries**, and so does it help those countries in explaining consumption-based emissions. It can be said is that, though the balance of fuel could help predict for some countries, it is not significant overall in the sense that the Mean Groups regressions examine.

Because Liddle (2018) [7] found that the share of fossil fuel in the energy mix of a country was significant in explaining consumption-based emissions, one could think that the balance of fuel could help in predictions. Yet, the results of the regressions run in this work (in particular, see regressions 12 to 21) show that the balance of fuel is not a key element to predict consumption-based emissions, in the context of this study with the chosen variables. Indeed, it is coherent with the idea that what increases consumption-based emissions is importing goods and services for which fossil fuels have been burnt outside of one country's borders.

Two things can be inferred from this. Firstly, the balance of fossil fuels could be significant for fossil duel producers in particular, even to explain transfer emissions, because of the pollution from the fuel extraction. Secondly, though fossil fuel might not be very significant in explaining transfer emissions, they could be significant in explaining consumption-based emissions because of the underlying territory-based distribution of emissions. Let us display a CCEMG regression in Table 5 below. There, as in the Liddle (2018) [7] regression, fossil_fuel is significant though there is only one independent variable, which is the logged form of fossil GDP.

The last result of this work is the one that focuses on the particular effect of GDP on consumption-based emissions. Succeeding in modelling consumption-based emissions using a fixed effect per country and a marginal effect determined by the GDP would be extremely convenient in the context of including consumption-based emissions to IAMs which model few macroeconomic data.

Yet, again, there is strong evidence against this possibility. In order to test this possibility, we would like to estimate the following model

$$\mathrm{emissions\_balance\_percent_{it}} = A * (logGDP_{it})^2 + B * logGDP_{it} + c_i \quad (3)$$

Table 5: CCEMG regression using the logged form of fossil GDP

Dependent variable:	log_territorial
log_gdp_fossil	0.836***
	(0.056)
y.bar	0.820***
	(0.175)
log_gdp_fossil.bar	-0.698***
	(0.091)
Constant	-1.857*
	(1.109)
Observations	1,330
R^2	0.999
CD p-value	0.3098
Note:	*p<0.1, **p<0.05, ***p<0.01

There are two possibilities to test this model. The first one would be to estimate its derived form in pooled OLS, i.e. the following equation, which would remove the country fixed effect to estimate.

$$\frac{\delta ratio_{it}}{\delta \log(GDP_{it})} = 2A * \delta \log(GDP_{it}) + B \qquad (4)$$

However, because of the of the possible misspecification of the model, the incremental growth rate of the emissions ratio often takes diverging values, which prevents any reasonable estimation of A and B.

This is why the retained form for this regression is that of Equation (5), which is estimated in pooled OLS. The results are given in Table 6 below.

$$\delta ratio_{it} = A\delta \log(GDP_{it})^2 + B\delta \log(GDP_{it}) \qquad (5)$$

Table 6 : Pooled OLS estimate testing quadratic effect of GDP

	Dependent variable:
	delta_ratio
delta_gdp	-55.595
	(49.676)
delta_gdp_square	3.146
	(2.746)
Observations	2,266
R^2	0.001
Adjusted R^2	-0.0003
Residual Std. Error	19.844 (df = 2264)
F Statistic	0.663 (df = 2; 2264)
Note:	*p<0.1, **p<0.05, ***p<0.01

When it comes to prediction, mean absolute error is 1 094 kgC02 per capita per year on the last five year of predictions, and the predictions are balanced to -17.96%.

Among the remarks that can be done to this model, one would be that the marginal effect of GDP is very low. For values of logged GDP that evolve between 6 and 12, and given that a country's GDP does not span through all the values, the effects explained by variations of GDP in this estimate would likely reach to the maximum plus or minus 10 points of percentage. In addition, this model does not allow for decoupling of emissions from GDP.

Finally, in order to assess more precisely the role of GDP in explaining and predicting consumption_based emissions and transfer emissions, Means Groups regressions numbered 32 to 38 try different model that could possibly suit. Yet, no one can reach satisfactory requirements that would hint a deeper effect. For more information, please refer to Annex A and/or the code itself.

In conclusion, one could say that**, apart from explaining and predicting territory-based emissions, GDP performs less effectively than a fixed effect to explain and predict transfer emissions**.

Discussion

Many elements of this work call for deeper discussion. First of all, because the work is still ongoing, the following elements could be added to the study. Adding serial correlation tests to the residuals of the various regressions would be an opportunity the time-dependent trend. Indeed, combined with the CD test, this method would be able to assess that residuals are cross-period and cross-national independent, which would help in qualifying the fitness of regressions.

Another point of discussion is that of the unaccounted emissions in the data. Indeed, though some countries are not included in NICE, they should be included in the prediction exercise, since there exists data for them, as well as the data for Taiwan, Yemen, Erytrea and Cuba, that could be recovered from another source.

The point about the missing data for consumption-based emissions is truly worthy of discussion. There miss 63 countries in the database from the Global Carbon Project which have no data about their consumption-based emissions. Here, the choice that is made is to assess the formula from the country with the closest profile. One might argue that other data could be found and harmonized in order to extend the database. However, this option has been tested, for example concerning some African countries which are treated by Wang et al. (2024) [28], for the countries both covered by this work and the Global Carbon Project's database, there are differences both in levels and in the variations from one period to another, which call for deeper work of harmonization before merging different databases of consumption-based (as well as territory-based) emissions. Indeed, accounting emissions is a complex process for which different methods apply.

When it come to assessing more precisely the fitness of each regression per country, which is clearly the next step of this work, one could think of the following method. Given that the time series span over 32 years, and that, in those grouped emissions, only between 20 and 25 are used to help balance the panel, one could think of applying the process individually per country in order to add more data for the country which allow this possibility. Then, it would be possible to split the dataset in three: the first years would be used to train different regressions, which would then be compared after a time lag of a few years in order to select some possible regressions. This is the current process. However, the third period would be used to observe whether the errors increase or not, which would thus be a sign of overfitting of the estimate on the training set. This would allow to prevent some risk of overfitting.

Another idea would be to scale up (respectively down) all the countries which are estimated above (respectively below) their true emissions on average, in order to reach a globally balanced prediction of consumption-based emissions over the evaluation set. The hypothesis could be specifically useful for models in which there are acknowledged uncaptured time-dependent or country dependent trends which could be compensated by rescaling the emissions.

In addition, one can ask questions about the relevance of comparing models like the fix ratio and other regressions which do not assume a distribution of territory-based emissions in the future. Indeed, such territory-based emissions would need to be modelled in order to predict the distribution of consumption-based emissions. Therefore, comparing all regressions using the same criterion of the mean absolute error over several years can be seen as too much simplifying, since errors would be compounded. One should argue that a measure of an error that would make sense would be one which encompasses the modelling of all the variables.

Alternatively, an answer that could be proposed to this interrogation would be that there exist ways to model emissions that are not predictions but trajectories, or scenarios, which are not meant to reflect the most probable issue, but rather an examined probability which is given to the model, and from which one would like to draw policy recommendations.

Conclusion

This work demonstrates that econometric panel methods can offer a robust framework for forecasting consumption-based CO_2 emissions at the country level. While simple models based on GDP or territorial emissions can provide a rough baseline, they fail to capture the complexity of carbon transfers embedded in international trade. The analysis reveals three key findings. First, it is generally acceptable for economic-climate models to neglect trade balances when using territorial emissions, but accounting for trade becomes essential when aiming to reconstruct or forecast consumption-based emissions via transfer emissions. Second, despite their apparent relevance, fuel trade balances do not significantly improve model accuracy, though they may help for some countries. Third, GDP alone is less useful than fixed effects in explaining variations in transfer emissions, underscoring the structural persistence of country-specific factors.

These results emphasize the importance of integrating structural trade imbalances and national specificities into emission forecasting. They also call for caution when relying solely on macroeconomic indicators, especially in policy contexts concerned with climate justice and redistribution. The methods developed in this study provide a transparent and adaptable econometric approach to long-term emission forecasting, and lay the groundwork for integrating such forecasts into broader climate policy models. Further work could explore hybrid approaches combining economic structure, machine learning, and scenario-based forecasting to enhance robustness and interpretability.

Annex A: Summary of the Mean Groups regressions completed

Regression ID	1	2	3	4	5	6	7	8
Results								
R^2	0,9923	0,9968	0,9992	0,998	0,9965	0.9971	0,987	0,979
CD p-value	4,51E-06	2,74E-10	1,30E-14	0,110	1,04E-06	4,58E-10	0,772	0,807
MAE	0,742	0,34	0,815	0,91	1,12	0,54	0,518	0,967
balance_percent	N/A	-0,1	N/A	-10,93	9,37	N/A	N/A	-7,65
Predicted variable								
territorial_emissions	1	0	0	0	0	0	0	0
log_territorial	0	0	1	0	0	1	0	0
consumption_emissions	0	0	0	0	0	0	0	0
log_consumption	0	1	0	1	1	0	0	0
transfer_emissions	0	0	0	0	0	0	0	0
emissions_balance_percent	0	0	0	0	0	0	0	1
Independent variables								
fixed_effect	1	0	0	0	1	0	0	0
territorial_emissions	0	0	0	0	0	0	0	1
log_territorial	0	1	0	0	0	0	0	0
emissions_pc.world	1	0	0	0	0	0	0	1
log_gdp	0	1	1	1	1	1	0	1
gdp	1	0	0	0	0	0	0	0
gdp.world	1	0	0	0	0	0	0	1
log_gdp.world	0	1	1	1	0	0	1	0
fossil_fuel_share	1	0	1	1	0	0	0	1
log_ffsh	0	0	0	0	1	1	0	0
trade_share	0	0	1	1	0	0	0	0
exports_gns_percent.world	0	0	0	0	0	0	0	1
industry_share.world	0	0	1	1	0	0	0	1
industry_share	0	0	1	1	0	0	0	1
log_industry_share	0	0	0	0	0	0	1	0
log_industry_share.world	0	0	0	0	0	0	1	0
log_emissions_pc.world	0	1	0	0	0	0	1	0
log_imports_gns_percent	0	1	0	0	1	0	1	0
log_exports_gns_percent	0	1	0	0	1	1	1	0
log_exports_gns%.world	0	1	0	0	1	0	1	0
log_imports_gns_%.world	0	0	0	0	1	1	0	0
trade_balance_gns	0	0	0	0	0	0	0	0
trade_balance_goods	0	0	0	0	0	0	0	0
imports_gns_percent	0	0	0	0	0	0	0	1
exports_gns_percent	0	0	0	0	0	0	0	1
fuel_imports_percent_gdp	0	0	0	0	0	0	0	0
fuel_exports_percent_gdp	0	0	0	0	0	0	0	0
imports_goods_percent	0	0	0	0	0	0	0	0
exports_goods_percent	0	0	0	0	0	0	0	0
trade_gns_percent.world	0	0	1	1	0	0	0	0
trade_balance_gns_percent	0	0	0	0	0	0	0	0
trade_balance_goods_perce	0	0	0	0	0	0	0	0
balance_fuel_percent_gdp	0	0	0	0	0	0	0	0

Regression ID	9	10	11	12	13	14	15	16
Results								
R^2	0,9108	0,831	0,890	0,997	0,9677	0,969	0,892	0,8725
CD p-value	1,47E-05	0	0	0,889	5,51E-03	0,722	0,211	7,45E-04
MAE	0,233	0,259	0,284	0,794	0,522	2,29	0,842	0,322
balance_percent	1,97	2,28	2,3	-17,96	-1,66	-48,3	-6,94	2,17
Predicted variable								
territorial_emissions	0	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0	0
consumption_emissions	0	0	0	0	0	0	0	0
log_consumption	0	0	0	0	0	0	0	0
transfer_emissions	0	0	0	0	0	0	0	0
emissions_balance_percent	1	1	1	1	1	1	1	1
Independent variables								
fixed_effect	1	1	1	0	0	0	0	0
territorial_emissions	0	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0	0
emissions_pc.world	0	0	0	0	0	0	0	0
log_gdp	0	0	0	0	0	0	0	0
gdp	0	0	0	0	0	0	0	0
gdp.world	0	0	0	0	0	0	0	0
log_gdp.world	0	0	0	0	0	0	0	0
fossil_fuel_share	0	0	0	0	0	0	0	0
log_ffsh	0	0	0	0	0	0	0	0
trade_share	0	0	0	0	0	0	0	0
exports_gns_percent.world	1	0	0	1	0	0	0	0
industry_share.world	0	0	0	0	0	0	0	0
industry_share	0	0	0	0	0	0	0	0
log_industry_share	0	0	0	0	0	0	0	0
log_industry_share.world	0	0	0	0	0	0	0	0
log_emissions_pc.world	0	0	0	0	0	0	0	0
log_imports_gns_percent	0	0	0	0	0	0	0	0
log_exports_gns_percent	0	0	0	0	0	0	0	0
log_exports_gns%.world	0	0	0	0	0	0	0	0
log_imports_gns_%.world	0	0	0	0	0	0	0	0
trade_balance_gns	0	0	0	0	0	0	0	0
trade_balance_goods	0	0	0	0	0	0	0	0
imports_gns_percent	1	0	1	1	1	1	0	0
exports_gns_percent	1	0	1	1	1	1	0	0
fuel_imports_percent_gdp	0	0	0	1	1	1	0	0
fuel_exports_percent_gdp	0	0	0	1	1	1	0	0
imports_goods_percent	0	0	0	0	0	1	0	0
exports_goods_percent	0	0	0	0	0	1	0	0
trade_gns_percent.world	0	0	0	0	0	0	0	0
trade_balance_gns_percent	0	1	0	0	0	0	1	0
trade_balance_goods_percen	0	0	0	0	0	0	1	1
balance_fuel_percent_gdp	0	0	0	0	0	0	1	1

Regression ID	17	18	19	20	21	22	23	24
Results								
R^2	0,8535	0,717	0,9427	0,9277	0,9387	0,993	0,991	0,993
CD p-value	1,12E-05	0,133	1,39E-04	1,86E-04	9,69E-03	0	0	0
MAE	0,288	0,38	0,377	0,38	0,523	0,863	0,713	0,504
balance_percent	2,71	3,5	-4,49	0,02	-8,27	13,33	3,13	7,62
Predicted variable								
territorial_emissions	0	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0	0
consumption_emissions	0	0	0	0	0	0	0	0
log_consumption	0	0	0	0	0	1	1	1
transfer_emissions	0	0	0	0	0	0	0	0
emissions_balance_percent	1	1	1	1	1	0	0	0
Independent variables								
fixed_effect	0	0	1	0	0	0	1	1
territorial_emissions	0	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0	1
emissions_pc.world	0	0	0	0	0	0	0	0
log_gdp	0	0	1	1	1	1	1	0
gdp	0	0	0	0	0	0	0	0
gdp.world	0	0	0	0	0	0	0	0
log_gdp.world	0	0	0	0	0	1	1	0
fossil_fuel_share	0	0	0	0	1	0	0	0
log_ffsh	0	0	0	0	0	1	0	0
trade_share	0	0	0	0	0	0	0	0
exports_gns_percent.world	0	0	0	0	0	0	0	0
industry_share.world	0	0	0	0	0	0	0	0
industry_share	0	0	0	0	0	0	0	0
log_industry_share	0	0	0	0	0	0	0	0
log_industry_share.world	0	0	0	0	0	0	0	0
log_emissions_pc.world	0	0	0	0	0	1	1	1
log_imports_gns_percent	0	0	0	0	0	0	0	0
log_exports_gns_percent	0	0	0	0	0	0	0	0
log_exports_gns%.world	0	0	0	0	0	0	0	0
log_imports_gns_%.world	0	0	0	0	0	0	0	0
trade_balance_gns	0	0	0	0	0	0	0	0
trade_balance_goods	0	0	0	0	0	0	0	0
imports_gns_percent	0	0	0	0	0	0	0	0
exports_gns_percent	0	0	0	0	0	0	0	0
fuel_imports_percent_gdp	0	0	0	0	0	0	0	0
fuel_exports_percent_gdp	0	0	0	0	0	0	0	0
imports_goods_percent	0	0	0	0	0	0	0	0
exports_goods_percent	0	0	0	0	0	0	0	0
trade_gns_percent.world	0	0	0	0	0	0	0	0
trade_balance_gns_percent	1	0	1	1	1	0	0	0
trade_balance_goods_perce	0	0	0	0	0	0	0	0
balance_fuel_percent_gdp	1	1	1	0	1	0	0	0

Regression ID	25	26	27	28	29	30	31
Results							
R^2	0,9922	0,9718	0,7480	0,9160	0,9442	0,9245	0,9843
CD p-value	1,85E-04	0	0	0	1,54E-15	0	0,317
MAE	0,623	0,459	0,333	0,237	0,459	0,36	0,751
balance_percent	-5,34	5,98	1,82	1,79	0,08	1,14	-2,65
Predicted variable							
territorial_emissions	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0
consumption_emissions	1	1	0	0	0	0	0
log_consumption	0	0	0	0	0	0	0
transfer_emissions	0	0	1	1	1	1	0
emissions_balance_percent	0	0	0	0	0	0	1
Independent variables							
fixed_effect	1	1	0	1	1	0	1
territorial_emissions	1	1	0	0	0	0	1
log_territorial	0	0	0	0	0	0	0
emissions_pc.world	1	1	0	0	0	0	1
log_gdp	0	0	0	0	1	1	1
gdp	1	0	0	0	0	0	0
gdp.world	1	0	0	0	0	0	1
log_gdp.world	0	0	0	0	0	0	0
fossil_fuel_share	0	0	0	0	0	0	1
log_ffsh	0	0	0	0	0	0	0
trade_share	0	0	0	0	0	0	0
exports_gns_percent.world	0	0	0	0	0	0	1
industry_share.world	0	0	0	0	0	0	1
industry_share	0	0	0	0	0	0	1
log_industry_share	0	0	0	0	0	0	0
log_industry_share.world	0	0	0	0	0	0	0
log_emissions_pc.world	0	0	0	0	0	0	0
log_imports_gns_percent	0	0	0	0	0	0	0
log_exports_gns_percent	0	0	0	0	0	0	0
log_exports_gns%.world	0	0	0	0	0	0	0
log_imports_gns_%.world	0	0	0	0	0	0	0
trade_balance_gns	1	0	1	1	1	1	0
trade_balance_goods	1	0	0	0	0	0	0
imports_gns_percent	0	0	0	0	0	0	1
exports_gns_percent	0	0	0	0	0	0	1
fuel_imports_percent_gdp	0	0	0	0	0	0	0
fuel_exports_percent_gdp	0	0	0	0	0	0	0
imports_goods_percent	0	0	0	0	0	0	0
exports_goods_percent	0	0	0	0	0	0	0
trade_gns_percent.world	0	0	0	0	0	0	0
trade_balance_gns_percent	0	0	0	0	0	0	0
trade_balance_goods_percent	0	0	0	0	0	0	0
balance_fuel_percent_gdp	0	0	0	0	0	0	0

Regression ID	32	33	34	35	36	37	38
Results							
R^2	0,8626	0,8627	0,9721	0,9717	0,8884	0,8827	0,9933
CD p-value	0	0	0	0	0	0	0
MAE	0,6	0,51	0,785	0,999	0,556	0,592	0,636
balance_percent	3,9	-1,46	-4,44	-22,52	-0,61	-1,99	-11,54
Predicted variable							
territorial_emissions	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0
consumption_emissions	0	0	1	1	1	0	0
log_consumption	0	0	0	0	0	0	1
transfer_emissions	0	0	0	0	0	1	0
emissions_balance_percent	1	1	0	0	0	0	0
Independent variables							
fixed_effect	1	1	1	1	1	1	1
territorial_emissions	0	0	0	0	0	0	0
log_territorial	0	0	0	0	0	0	0
emissions_pc.world	0	0	0	0	0	0	0
log_gdp	1	0	1	0	1	0	1
gdp	0	1	0	1	0	1	0
gdp.world	0	1	0	1	0	1	0
log_gdp.world	1	0	1	0	1	0	1
fossil_fuel_share	0	0	0	0	0	0	0
log_ffsh	0	0	0	0	0	0	0
trade_share	0	0	0	0	0	0	0
exports_gns_percent.world	0	0	0	0	0	0	0
industry_share.world	0	0	0	0	0	0	0
industry_share	0	0	0	0	0	0	0
log_industry_share	0	0	0	0	0	0	0
log_industry_share.world	0	0	0	0	0	0	0
log_emissions_pc.world	0	0	0	0	0	0	0
log_imports_gns_percent	0	0	0	0	0	0	0
log_exports_gns_percent	0	0	0	0	0	0	0
log_exports_gns%.world	0	0	0	0	0	0	0
log_imports_gns_%.world	0	0	0	0	0	0	0
trade_balance_gns	0	0	0	0	0	0	0
trade_balance_goods	0	0	0	0	0	0	0
imports_gns_percent	0	0	0	0	0	0	0
exports_gns_percent	0	0	0	0	0	0	0
fuel_imports_percent_gdp	0	0	0	0	0	0	0
fuel_exports_percent_gdp	0	0	0	0	0	0	0
imports_goods_percent	0	0	0	0	0	0	0
exports_goods_percent	0	0	0	0	0	0	0
trade_gns_percent.world	0	0	0	0	0	0	0
trade_balance_gns_percent	0	0	0	0	0	0	0
trade_balance_goods_percent	0	0	0	0	0	0	0
balance_fuel_percent_gdp	0	0	0	0	0	0	0

Note about Annex A:

The mean absolute error (MAE) is averaged over 5 years of prediction, between t+6 and t+10, where t is the last year of training data.

The variable balance_percent corresponds to the error in the total of global CO2 emissions predicted by the regression. When it is positive, the true total global emissions are higher than the estimated ones. When it is negative, the true global emissions are lower than the estimated ones.

The following lines describe each variable used in Annex A. They are all indexed per year.

Predicted variable	
territorial_emissions	Territory-based emissions per capita in tCO2
log_territorial	Logged territory-based emissions per capita in tCO2
consumption_emissions	Consumption-based emissions per capita in tCO2
log_consumption	Logged consumption-based emissions per capita in tCO2
transfer_emissions	consumption_emissions – territorial_emissions
emis-	transfer_emissions/territorial_emissions
Independent variables	
fixed_effect	Adding a fixed effect per country to the formula
territorial_emissions	Territory-based emissions per capita in tCO2
log_territorial	Logged territory-based emissions per capita in tCO2
emissions_pc.world	Global average per capita of fossil CO2 emissions in tCO2
log_gdp	Logged GDP per capita (in
gdp	GDP per capita, PPP (constant 2021 international USD)
gdp.world	Global GDP per capita, PPP (constant 2021 international $)
log_gdp.world	ln(gdp.world)
fossil_fuel_share	Fossil fuel energy consumption (% of total)
log_ffsh	ln(fossil_fuel_share)
trade_share	Imports + exports as percentage of GDP
exports_gns_percent.world	Global exports as percentage of global GDP
industry_share.world	Global industry (including construction), value added (%GDP)
industry_share	Industry (including construction), value added (%GDP)
log_industry_share	ln(industry_share)
log_industry_share.world	ln(industry_share.world)
log_emissions_pc.world	ln(emissions_pc.world)
log_imports_gns_percent	ln(imports_gns_percent)
log_exports_gns_percent	ln(exports_gns_percent)
log_exports_gns%.world	ln(exports_gns_percent.world)
log_imports_gns_%.world	ln(exports_gns_percent.world)
trade_balance_gns.pc	Trade balance of goods and services per capita in constant 2015 constant USD
trade_balance_goods.pc	Trade balance of goods per capita in constant 2021 USD
imports_gns_percent	Imports as percentage of GDP
exports_gns_percent	Exports as percentage of GDP
fuel_imports_percent_gdp	Fuel exports (%GDP). Fuels comprise the commodities in SITC section 3 (mineral fuels, lubricants and related materials)
fuel_exports_percent_gdp	Fuel exports as percentage of GDP
imports_goods_percent	Goods imports as percentage of GDP
exports_goods_percent	Goods exports as percentage of GDP

trade_gns_percent.world	Global trade as percentage of global GDP
trade_balance_gns_percent	Trade balance of goods and services as percentage of GDP
trade_balance_goods_percent	Trade balance of goods as percentage of GDP
balance_fuel_percent_gdp	Trade balance of fuels as percentage of GDP

Annex B: Best predictions of consumption-based emissions

country	(10)	(11)	(17)	(20)	fix	min_error	best_reg_2	closest_country
ABW							fix	DOM
AFG							fix	NPL
AGO							fix	CMR
ALB	0,050	0,094	0,096	0,269	0,227	0,050	(10)	ALB
ARE			4,711	3,853	1,341	1,341	fix	ARE
ARG	0,100	0,100	0,126	0,095	0,126	0,095	(20)	ARG
ARM			0,299	0,814	0,120	0,120	fix	ARM
AUS	0,311	0,350	0,527	2,131	0,235	0,235	fix	AUS
AUT	0,372	0,804	0,165	1,100	0,621	0,165	(17)	AUT
AZE	0,059	0,119	0,157	0,956	0,569	0,059	(10)	AZE
BDI							(10)	MOZ
BEL	1,167	0,524	3,896	0,590	4,140	0,524	(11)	BEL
BEN	0,181	0,201	0,249	0,298	0,163	0,163	fix	BEN
BFA	0,028	0,116			0,096	0,028	(10)	BFA
BGD	0,229	0,208			0,185	0,185	fix	BGD
BGR	0,248	0,238	0,634	0,271	0,272	0,238	(11)	BGR
BHR			4,756	2,160	2,543	2,160	(20)	BHR
BHS							fix	DOM
BIH							(10)	ALB
BLR	1,449	1,248	0,837	1,541	1,590	0,837	(17)	BLR
BLZ							fix	GTM
BOL	0,073	0,080	0,024	0,097	0,173	0,024	(17)	BOL
BRA	0,046	0,045	0,021	0,182	0,118	0,021	(17)	BRA
BRB							fix	DOM
BRN	2,966	5,431			2,488	2,488	fix	BRN
BTN							fix	LKA
BWA	1,856	2,069	2,351	2,259	2,238	1,856	(10)	BWA
CAF							fix	CMR
CAN	2,226	2,202	2,182	2,179	1,710	1,710	fix	CAN
CHE	4,871	4,574	5,793	3,811	5,325	3,811	(20)	CHE
CHL	0,204	0,307	0,087	0,438	0,221	0,087	(17)	CHL
CHN	0,214	0,160	0,252	0,348	0,346	0,160	(11)	CHN
CIV	0,088	0,165	0,169	0,335	0,081	0,081	fix	CIV
CMR	0,026	0,023	0,035	0,097	0,019	0,019	fix	CMR
COD							fix	CMR
COG							fix	CMR
COL	0,041	0,047	0,089	0,467	0,066	0,041	(10)	COL
COM							(17)	TZA
CPV							(11)	GHA
CRI	0,210	0,268	0,396	0,509	0,107	0,107	fix	CRI
CUB							#N/A	
CYP	1,260	2,200	0,624	1,434	1,628	0,624	(17)	CYP
CZE	0,660	0,643	0,873	0,919	1,001	0,643	(11)	CZE

DEU	0,428	0,537	0,352	1,009	0,274	0,274	fix	DEU
DJI							fix	KEN
DNK	1,313	0,434	2,472	0,841	1,533	0,434	(11)	DNK
DOM	0,634	4,590	0,901	7,271	0,439	0,439	fix	DOM
DZA							fix	EGY
ECU	0,167	0,348	0,250	0,062	0,252	0,062	(20)	ECU
EGY	0,137	0,112	0,117	0,118	0,091	0,091	fix	EGY
ERI							#N/A	
ESP	0,373	1,080	0,251	1,260	0,193	0,193	fix	ESP
EST	1,397	1,197	1,233	1,972	1,433	1,197	(11)	EST
ETH					0,016	0,016	fix	ETH
FIN	0,682	0,334	0,784	0,536	0,668	0,334	(11)	FIN
FJI							(10)	VNM
FRA	0,358	0,388	0,368	0,653	0,126	0,126	fix	FRA
GAB							fix	CMR
GBR	0,785	0,517	1,036	0,506	0,968	0,506	(20)	GBR
GEO	0,868	1,106	0,382	0,795	0,450	0,382	(17)	GEO
GHA	0,055	0,050			0,081	0,050	(11)	GHA
GIN					0,142	0,142	fix	GIN
GMB							fix	TGO
GNB							(10)	BFA
GNQ							fix	CMR
GRC	1,502	1,071	0,462	1,261	1,320	0,462	(17)	GRC
GTM	0,227	0,523	0,231	0,207	0,170	0,170	fix	GTM
GUY							(17)	BRA
HKG			2,228	1,080	3,268	1,080	(20)	HKG
HND	0,179	0,107			0,282	0,107	(11)	HND
HRV	0,717	0,260	0,616	0,350	0,672	0,260	(11)	HRV
HTI							fix	JAM
HUN	0,200	0,453	0,134	0,862	0,143	0,134	(17)	HUN
IDN	0,048	0,113	0,052	0,151	0,242	0,048	(10)	IDN
IND	0,010	0,028	0,020	0,049	0,012	0,010	(10)	IND
IRL	1,191	3,577	1,015	7,830	0,367	0,367	fix	IRL
IRN	0,207	0,292			0,259	0,207	(10)	IRN
IRQ							fix	ARM
ISL							(11)	SWE
ISR	0,389	0,867			0,417	0,389	(10)	ISR
ITA	0,580	0,652	0,301	0,888	0,120	0,120	fix	ITA
JAM					0,262	0,262	fix	JAM
JOR	0,091	0,151	0,280	0,119	0,106	0,091	(10)	JOR
JPN	0,858	0,897	0,351	0,913	0,615	0,351	(17)	JPN
KAZ	1,596	0,552	2,722	0,767	1,992	0,552	(11)	KAZ
KEN	0,047	0,096			0,044	0,044	fix	KEN
KGZ	0,232	0,457	0,295	0,692	0,511	0,232	(10)	KGZ
KHM	1,535	0,835			0,146	0,146	fix	KHM
KOR	0,127	0,207	0,218	0,818	1,019	0,127	(10)	KOR

KWT					2,019	2,019	fix	KWT
LAO					1,850	1,850	fix	LAO
LBN							fix	ARM
LBR							(10)	BFA
LBY							fix	TUN
LCA							fix	DOM
LKA					0,073	0,073	fix	LKA
LSO							(20)	NAM
LTU	0,492	0,475	3,000	0,469	0,301	0,301	fix	LTU
LUX	1,426	4,269	4,050	1,049	0,676	0,676	fix	LUX
LVA	1,293	2,009	2,355	1,293	1,220	1,220	fix	LVA
MAC							(20)	HKG
MAR	0,071	0,037	0,053	0,214	0,173	0,037	(11)	MAR
MDA							(17)	UKR
MDG			0,024	0,029	0,028	0,024	(17)	MDG
MDV							(10)	IRN
MEX	0,145	0,215	0,175	0,139	0,184	0,139	(20)	MEX
MKD							(10)	ALB
MLI							(10)	BFA
MLT	10,505	8,852	8,973	7,103	13,845	7,103	(20)	MLT
MMR							fix	KHM
MNE							(10)	ALB
MNG	0,834	1,128			0,230	0,230	fix	MNG
MOZ	0,200	0,382	0,370	0,319	0,327	0,200	(10)	MOZ
MRT							fix	CIV
MUS							fix	KEN
MWI					0,018	0,018	fix	MWI
MYS	0,066	0,173	0,126	0,943	0,160	0,066	(10)	MYS
NAM	1,774	2,257	1,702	1,205	2,099	1,205	(20)	NAM
NER							(10)	BFA
NGA					0,046	0,046	fix	NGA
NIC	0,197	0,144	0,151	0,055	0,055	0,055	fix	NIC
NLD	3,604	3,168	2,916	5,361	0,606	0,606	fix	NLD
NOR					0,166	0,166	fix	NOR
NPL	0,231	0,263			0,197	0,197	fix	NPL
NZL	0,163	0,085	0,359	0,178	0,344	0,085	(11)	NZL
OMN	0,242	0,253	0,568	0,384	0,358	0,242	(10)	OMN
PAK	0,021	0,015	0,035	0,020	0,039	0,015	(11)	PAK
PAN	2,438	3,250	2,222	3,396	2,346	2,222	(17)	PAN
PER	0,033	0,054	0,076	0,309	0,046	0,033	(10)	PER
PHL	0,024	0,027	0,118	0,082	0,093	0,024	(10)	PHL
PNG							fix	KHM
POL	0,327	0,102	0,225	0,079	0,388	0,079	(20)	POL
PRT	3,495	7,498	0,811	3,209	1,991	0,811	(17)	PRT
PRY	0,103	0,268	0,319	0,463	0,041	0,041	fix	PRY
PSE							(10)	JOR

PYF							#N/A	
QAT					2,095	2,095	fix	QAT
ROU	0,723	0,293	0,422	0,318	0,575	0,293	(11)	ROU
RUS	0,307	0,076	0,440	0,251	0,950	0,076	(11)	RUS
RWA	0,036	0,039	0,039	0,030	0,037	0,030	(20)	RWA
SAU	1,581	1,767	0,303	2,422	1,805	0,303	(17)	SAU
SDN							(11)	MAR
SEN	0,032	0,044	0,025	0,070	0,044	0,025	(17)	SEN
SGP	1,056	14,465	1,413	5,947	5,200	1,056	(10)	SGP
SLB							fix	KHM
SLE							fix	TGO
SLV							fix	GTM
SRB							(10)	ALB
STP							fix	CMR
SUR							(17)	BRA
SVK	0,157	0,255	0,192	1,099	0,310	0,157	(10)	SVK
SVN	1,768	1,523	2,168	1,700	1,296	1,296	fix	SVN
SWE	0,711	0,447	1,133	0,486	0,554	0,447	(11)	SWE
SWZ							(20)	NAM
SYR							(10)	JOR
TCD							fix	CMR
TGO	0,399	0,392			0,387	0,387	fix	TGO
THA	0,134	0,134	0,080	0,339	0,390	0,080	(17)	THA
TJK	0,530	0,846			0,318	0,318	fix	TJK
TKM							(10)	KGZ
TLS							fix	KHM
TON							fix	KHM
TUN	0,554	0,574	2,370	0,285	0,227	0,227	fix	TUN
TUR	0,401	0,295	0,393	0,313	0,797	0,295	(11)	TUR
TWN							#N/A	
TZA	0,092	0,090	0,062	0,086	0,089	0,062	(17)	TZA
UGA	0,046	0,059	0,008	0,024	0,069	0,008	(17)	UGA
UKR	0,326	0,346	0,324	0,382	0,451	0,324	(17)	UKR
URY	0,472	0,367	0,680	0,259	0,399	0,259	(20)	URY
USA	0,793	0,824	0,543	0,599	0,773	0,543	(17)	USA
UZB							(10)	KGZ
VCT							fix	DOM
VNM	0,219	0,493	1,428	0,502	0,615	0,219	(10)	VNM
VUT							fix	KHM
WSM							fix	KHM
YEM							#N/A	
ZAF	0,106	0,132	0,666	0,144	0,063	0,063	fix	ZAF
ZMB	0,340	0,411	0,544	0,396	0,260	0,260	fix	ZMB
ZWE			0,018	0,025	0,035	0,018	(17)	ZWE

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