The impact of green policies on carbon inequalities in Italy: A macrosimulation approach

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May 2024

Abstract

In this study, we analyze the effects of a combination of green transition and social policies on consumption-based emissions, carbon inequality and income inequality across households for Italy. We employ a macrosimulation approach using a new version of the Eurogreen model (Cieplinski et al., 2021; D'Alessandro et al., 2020), an input-output demand-led ecological macroeconomic model that exhibits stock-flow consistency, dynamically endogenous technical change, a detailed labour market structure, and two novel features. On the one hand, the individuals-based demographic structure is now integrated with a households module, with 100 households differentiated across the 20 Italian regions and income quintiles, which exhibit different income composition and consumption patterns. This level of heterogeneity allows for a better depiction of intranational disparities and a more detailed treatment of carbon and energy footprints. On the other hand, the correspondence between monetary and energy flows can now be tracked with more precision, thanks to the integration of physical-energy input-output tables, while energy sources are differentiated across 7 types, which allows for a better estimation of energy intensities and emissions' factors. In this framework, we simulate three policies: the introduction of a carbon tax, the tightening of emissions' permits caps, and the redistribution of fiscal carbon revenues to low-income families. We observe a trade-off between environmental and social goals, but we also find that a redistribution policy achieves strong reductions in both income and carbon inequalities, without high costs in terms of lower emissions' reductions.

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1 Introduction

Climate change does not affect everyone in the same way, neither do the green transition policies envisaged to avert it. Consumption-based measures of greenhouse gas (GHG) emissions allow to have a better picture of the environmental impact of economic activity and standards of living, and to better understand carbon inequality. This is because consumption-based measures trace emissions along global supply chains (Davis & Caldeira, 2010), and allow to identify carbon footprints across different population groups (Gore, 2021; Ivanova & Wood, 2020). Carbon inequalities across sub-national regions are of particular interest (Kilian et al., 2023) to have a clearer picture of the effect of inequality in climate change, of the effects of climate policies on inequality, and of the required social transformations to achieve simultaneously ecological and social goals. In this study, we follow the approach of integrating input-output matrices with household consumption patterns to analyze disparities in emissions from household consumption across subnational regions in Italy.

Italy exhibits some of the highest regional disparities among OECD countries in household income and unemployment (International Energy Agency, 2023). Regional differences are also prevalent for carbon emissions and energy consumption (for Climate, 2022), with consumption-based emissions concentrated in Northern regions (Algieri et al., 2022), and big disparities in terms of energy poverty risk, renewable energy generation, and exposure to extreme climate events (International Energy Agency, 2023). Thus, climate change will deepen regional inequalities and affect disproportionally certain population groups in Italy, through its differentiated effects across regions, productive sectors, and income groups (Spano & Mereu, 2020). On the other hand, policies that purport to reduce emissions can have adverse distributional impacts (Vandeplas et al., 2022).

In this context, we assess how regional inequalities in Italy—–in income and consumption-based emissions—–will respond to different market-based policies to reduce emissions. We use macrosimulations with a new version of the Eurogreen model for Italy '(Cieplinski et al., 2021; D'Alessandro et al., 2020). Eurogreen is a data-driven ecological macroeconomic model based on a detailed input-output structure with demand-led growth, that allows to analyze simultaneously macroeconomic and environmental variables in a system dynamics framework. It includes a stochastic endogenous process of technical change, by which technical input-output coefficients and labor productivity change dynamically. The new version of the model includes two novelties that allow for an analysis of households' income and carbon inequalities across regions. On the one hand, there are 100 representative households, differentiated by region and income quintiles, which exhibit different income source compositions and consumption patterns. On the other hand, monetary and physical-energy input-output matrices are integrated, which provides a link between energy sources, productive structure, and emissions. Moreover, the new version expands the sectoral classification, providing a more detailed structure with regards to the energy sectors.

In this framework, we simulate three alternative scenarios: first, the introduction of a carbon tax, second, a faster reduction in the amount of total emissions' allowances of the EU Emissions Trading Scheme, and third, a redistribution of fiscal carbon revenues from the two policies towards low income families. The simulations show a trade-off between ecological and social goals, as periods of reductions in emissions are generally associated with increasing inequality, both in income and carbon terms. We also find that the combination of both market-based policies achieves the best results in terms of emissions' reductions. On the other hand, the redistribution policy implies a less strong reduction in emissions, but it achieves significant reductions in both inequality indicators with respect to all the other scenarios.

The next section describes the methodology, with a brief description of the Eurogreen model, and a detailed presentation of the two novelties, the households module and the energy module, as well as of the policies implemented in the simulations. The last section presents and discusses the results.

2 Methodology

To analyze the impact of policies on consumption-based emissions and carbon inequality we conduct macrosimulations using Eurogreen, an Integrated Assessment Model (IAM) for Italy. IAMs are quantitative macroeconomic models that integrate economic and ecological spheres, and use scenario analysis to explore different pathways for climate change and energy transition. Given their integrated nature, IAMs capture the interdependence between different ecological, economic and social processes, so they can portray the effects of actions and policies accounting for feedback loops in a system dynamics framework. Thus, IAMs are highly versatile and suitable for the analysis of a wide range of issues (Proctor, 2023).

2.1 The Eurogreen model

The Eurogreen model integrates a dynamic input-output structure into a macroeconomic demand-led model, following post-Keyensian macroeconomic theory and guaranteeing stock-flow consistency. The model exhibits a high degree of heterogeneity, since it is composed by 21 sectors,[1] 24 types of individuals differentiated by gender, skill and occupational category, plus children and capitalists, and 100 households differentiated by region and income quintile. Outstanding features of the model are an endogenous stochastic process of technical change and a detailed labour market structure. Regarding technical change, the relative evolution of labour costs and intermediate inputs costs determines each period different probabilities for firms of developing either labour-saving or resource-saving innovations.

[1] The sectors are: 1) agriculture; 2) mining; 3) manufacturing; 4) petroleum refining; 5) manufacturing of vehicles; 6) electricity; 7) gas; 8) heat; 9) water; 10) construction; 11) trade; 12) transport; 13) hospitality; 14) information and communication technologies; 15) finance; 16) real estate; 17) professional services; 18) public administration and defense; 19) education; 20) health; and 21) households' production.

The implementation of these technologies, instead, governs the dynamics of labour productivity and input-output coefficients over time. With regards to labour market, labour supply is determined by the expected incomes of entering, remaining, or exiting the labour force, depending on the occupational category of individuals, and skill composition responds to skill-specific unemployment rates, such that workers move to skills higher job prospects. One the other hand, labour demand is determined by expected demand and labour productivity in a Keynesian way, while skill composition of labour supply is linked to the evolution of labour productivity. Wage dynamics, on the contrary, is affected by sector-specific labour productivity, gender- and skill-specific employment rates, and overall inflation and unemployment rates, as to capture the effects of firms' labour costs, workers' bargaining power, and macroeconomic conditions affecting general cost of living and bargaining power.

Firms set basic prices as a mark-up over unit labour and capital costs (wages, social security contributions and depreciation), and the mark-up evolves over time responding to the difference between current and initial rate of capacity utilization, to capture the price effects of higher demand. Carbon costs, on the other hand, enter into purchaser prices, which also include trade and transport margins. Each sector's price reacts to prices in the other sectors following the input-output structure of the Leontief price model (Miller & Blair, n.d.). On the other hand, investment plans depend on the difference between actual and normal rate of capacity utilization, following the capital stock adjustment principle. Although the model is demand led, there is the possibility of supply bottlenecks coming from capacity utilization or labor constraints. These supply constraints are accommodated by increasing the imported share of the different final demand components (consumption, government spending and investment).

The model is calibrated for 2010 (the initial year for the simulations) using data from different sources. The World Input-Output Database (WIOD) is used for the input-output structure, as well as output, value added and final demand. EU-KLEMS is used for the sectoral composition of employment, productivity, investment, and other variables differentiated by sector. EU-SILC is used for computing the wage structure. For other variables the main source is Eurostat. Now we expand on the description of the households and energy modules, which are the main elements for the computation of consumption-based emissions and carbon inequality.

2.2 The households module

The demographic structure of Eurogreen (Cieplinski et al., 2021; D'Alessandro et al., 2020) is based on a set of individual categories. Individuals were differentiated in 5 age cohorts , 2 genders, 3 skill levels, and 4 occupational categories. All these are working class individuals, to which a class of capitalists is added, that is not differentiated by gender nor skill, and are assumed as non working.

Based on these individual categories, households are defined as income-pooling entities, differentiated across the 20 Italian regions and 5 income quintiles. Accordingly, each household can be considered as representative of the demographic structure of a particular region-quintile. This demographic structure is computed from Survey of Household Income and Wealth by the Bank of Italy (SHIW) for 2010, the base year of the model. The individuals of that survey are classified according to the individual categories of Eurogreen in the following way:

- Age cohort: less than 14, 15 to 24, 25 to 44, 45 to 64, and more than 65 years old. The skill and occupational categories are only relevant for adult population, those 15 years or older.
- Gender: male and female.
- Skill level (educational attainment): None, Primary school certificate, and Lower secondary school certificate for low skill; Vocational secondary school diploma, Upper secondary school diploma for medium skill; 3-year university degree/higher education diploma, 5-year university degree, postgraduate qualification for high-skill.
- Occupational category: employed, unemployed, out of labour force, and retired.
- Capitalists: are defined as those in the top 1% of personal income distribution, using as sample weights the household weights multiplied by the number of members of the household.

er each region, quintiles are defined according to households' equivalent adult income, computed using a modified-modified OECD scale: A value is assigned to each household member (1 for the household head, 0.5 for non-household head adults, and 0.3 for children), the values of all member are summed-up, and finally, total household income is divided by that sum. The modification is that adults are defined as those 18 years or older, while the original OECD modified scale adults are 15 years or older.[2]

For each one of the 26 individuals' categories, the shares of the population per region-quintile are computed as:

$$\begin{aligned}
\pi^{k}_{s,g,RQ} &= \frac{N^{k}_{s,g,RQ}}{N^{k}_{s,g}} \\
\pi^{F}_{g,RQ} &= \frac{N^{F}_{g,RQ}}{N^{F}_{g}} \\
\pi^{cap}_{RQ} &= \frac{N^{cap}_{RQ}}{N^{cap}}
\end{aligned} \tag{1}$$

Where RQ denotes a particular combination of region and quintile, N is the total popu-

[2] Caveat: This is done to allow for an equivalent definition in the expenditure survey, whose microdata does not include a variable for age but for different cohorts, the first one corresponding to people from 0 to 17 years old.

lation of a particular category given by subscripts and superscripts: $s \in \{low, middle, high\}$ and $g \in \{f, m\}$ for skills and genders, superscripts $k \in \{E, U, OLF, P\}$, F and cap for the employed, unemployed, out of labour force, retired, children and capitalist populations.

In the model there are different types of incomes, which are allocated to each individual category based on specific rules, and then reallocated across households using the demographic shares of equation 1.

Labour income

Let $T^{I,k}_{s,g}$ and $T^{S,k}_{s,g}$ denote the progressive income tax and social security contributions for each $k \in \{E, U, P\}$. The the net labour income of the employed of gender g and skill level s, comes from deducting social security contributions and taxes to the Gross Wage Bill: $NWB_{s.g} = GWB_{s,g} - T^{I,E}_{s,g} - T^{S,E}_{s,g}$. The Net Wage Bill for region-quintile RQ is computed as a weighted sum across genders and skills for each RQ, the weights given by the shares of the relevant individual categories in RQ:

$$NWB_{RQ} = \sum_{s} \sum_{g} \pi^{E}_{s,g,RQ} NWB_{s,g} \tag{2}$$

Unemployment benefits

Gross Unemployment Benefits $GUB_{s,g}$ are computed based on past labour income, applying a replacement rate to the wages of the relevant individual category. Denoting by $tau^{S,E}$ the progressive tax rate on the unemployed, Net Unemployment Benefits per region-quintile RQ are computed again using the relevant individual categories in RQ:

$$NUB_{RQ} = \sum_{s} \sum_{g} \pi^{U}_{s,g,RQ} GUB_{s,g} (1 - \tau^{S,E}) \tag{3}$$

Pensions

The pension-wage ratio for each region-quintile is computed as:

$$pw_{RQ} = \frac{\overline{ytp}_{RQ}}{\overline{yl}_{RQ}} \tag{4}$$

With $\overline{ytp}_{RQ}$ and $\overline{yl}_{RQ}$ denoting the average *income from pensions and arrears* and the average *payroll income* respectively, computed from survey data using sampling weights. Pension transfers are assumed to vary in proportion to the wages of employed workers of the same skill group. Consequently, the gross pension benefit per region-quintile is given by:

$$GPB_{RQ} = pw_{RQ} \cdot \frac{GWB_{RQ}}{N^E_{RQ}} \cdot N^P_{RQ} \tag{5}$$

As with unemployment benefits, for each gender-skill population group pensions are assumed to be proportional to the labour income of that group, so Net Pension Benefits per region-quintile are:

$$NPB_{RQ} = GPB_{RQ}(1 - \tau^{S,E}) \tag{6}$$

Financial income

Financial income is determined by skill levels in the model and is not affected by occupational categories. Low skilled workers hold only deposits that do not pay interest, so they do not receive financial income. Middle skill individuals hold deposits and bonds that pay an interest, and high-skill individuals hold deposits, bonds, and equities. To get its allocation among regions-quintiles, first the share of non-capitalist adult population for each region-quintile in the total population by skill and gender is defined as:

$$\pi_{s,g,RQ} = \sum_k \pi^k_{s,g,RQ} N^k_{s,g}/N_{s,g} = \sum_k N^k_{s,g,RQ}/N_{s,g} \tag{7}$$

Using these shares, summing across skills and genders, adding the Gross Financial Income of capitalists, and applying the flat tax rate on financial income τ^F, the total Net Financial Income per region-quintile is defined as:

$$GFI_{RQ} = (1 - \tau^F) \cdot \left(\sum_s \sum_g \pi_{s,g,RQ} \cdot NFI_{s,g} + \pi^{cap}_{RQ} \cdot GFI^{cap} \right) \tag{8}$$

Mixed income

Mixed income is distributed among regions-quintiles according to

$$mI_{RQ} = MixedIncome \cdot \frac{ym_{RQ} + yca_RQ}{\sum_{RQ}(ym_{RQ} + yca_{RQ})} \tag{9}$$

With $MixedIncome$ denoting the total value in National Accounts, and ym and yca respectively denoting net self-employment income and income from real estate in the survey.

Other social protection transfers

Other transfers are not taxable. Sick and disability benefits are paid in equal amounts to all working-age adults (hence excluding children, the retired and capitalists), independent of skill level and gender, as the number of actual recipients is not modelled. The amount per person (sd) is calculated from the COFOG database for the initial period, and is subsequently updated according to inflation.

$$SD_{RQ} = sd \cdot \sum_s \sum_g \sum_k \pi^k_{s,g,RQ} N^k_{s,g} \tag{10}$$

Residual benefits go to low skilled individuals out of the labour force; denoting rb the residual benefits per person:

$$RB_{RQ} = rb \cdot \sum_g \pi^{OLF}_{low,g,RQ} L^{OLF}_{low,g} \tag{11}$$

Child benefits per region-quintile are distributed according to the share of children in the population:

$$FC_{RQ} = fc \cdot \sum_g \pi^F_{g,RQ} N^F_g \tag{12}$$

Total disposable income

Total disposable income per region-quintile is defined as:

$$\begin{aligned} YD_{RQ} =& NWB_{RQ} + NUB_{RQ} + NPB_{RQ} + NFI_{RQ} + mI_{RQ} \\ &+ SD_{RQ} + RB_{RQ} + FC_{RQ} + CY_{RQ} \end{aligned} \tag{13}$$

Where CY_{RQ} is the net income derived from carbon policies as will be explained below. To derive average household incomes, the totals are divided by the number of households per region and quintile: $YD^{HH}_{RQ} = YD_{RQ}/numHH_{RQ}$. These, in turn, are calibrated so that average household incomes in the model for the base year are equal to the observed average household incomes in the survey using sample weights. Following Jackson and Victor (2020), we assume that the expected disposable income at time t, $YD^{HH,e}$, is a linear extrapolation of past income growth.

To determine the level of consumption, the average propensity to consume out of income is computed as the ratio between total expenditure and disposable income in the survey, but the values are re-scaled so that aggregate consumption per region and quintile matches the levels observed in National Accounts data from Istat. In each period, the propensities to consume α_{RQ} vary proportionally to real expected household income, following per region a linear interpolation of the initial values of the five respective quintiles. Then, this propensity to consume is applied to nominal expected disposable income to derive total consumption per household in nominal terms

$$C_{RQ}^{HH} = \alpha_{RQ} YD^{HH,e} \tag{14}$$

Total consumption is then split across 16 different consumption goods based on the COICOP classification.[3] The expenditure shares on each consumption category for each region and quinitile are computed using the Household Budget Survey from Istat, as an average for the years 2014 to 2017, and then are adjusted using the RAS algorithm so that total consumption matches values from Istat National Accounts.[4]

The expenditure shares per consumption goods (the 16 COICOP categories) are then converted into expenditure shares per productive sectors (the 21 NACE industries) using a COICOP-NACE bridge matrix.[5] As it is done for propensities to consume, in each period the expenditure shares vary proportionally to real expected household income, following per region a linear interpolation of the initial values of the five respective quintiles. Moreover,

[3]The consumption categories are: 1) Food and non-alcohol beverages; 2) Alcoholic beverages, tobacco and narcotics; 3) Clothing and footwear; 4) Housing (Actual and imputed rentals, maintenance, repair and security of the dwelling); 5) Water supply and miscellaneous services relating to the dwelling; 6) Electricity, gas and other fuels; 7) Furnishing, household equipment and routine households maintenance; 8) Health; 9) Private transport; 10) Transport services; 11) Communications; 12) Recreation and culture; 13) Education; 14) Restaurants and hotels; 15) Personal care; and 16) Other

[4]The full procedure to compute expenditure shares is the following: 1) average household expenditure shares per region and quintile are computed from the HBS for years 2014 to 2017, using sample weights, and the average across the four years is computed; 2) the aggregate total expenditure per region and COICOP category is obtained from Istat; 2.1) this requires an intermediate step, since data on aggregate total expenditure is not available for certain disaggregated COICOP categories of Eurogreen (rental, water and electricity; vehicles and transport; personal care and other), so to obtain these values, a RAS algorithm is applied using the computed expenditure shares from the survey HBS and rescaling them to totals for the relevant COICOP category per region; 3) the aggregate household expenditure per region and quintile is computed from HBS, using grossing-up sample weights; 4) the totals in (3) are re-scaled using a conversion factor such that total expenditure per region (the sum across quintiles) computed from HBS equals total expenditure per region from aggregate Istat data; 5) the values from (2) of total expenditure per region and COICOP category are used as row constraints, while the values from (5) of total expenditure per region and quintile are used as column constraints, in a RAS algorithm to adjust the original expenditure shares in (1) to match aggregate values of consumption from Istat National Accounts.

[5]The procedure is as follows: 1) The bridge matrix for Italy developed by Cazcarro et al. (2022) is used as a Benchmark, aggregating their 47 COICOP categories and 64 NACE sectors into the 16 and 21 respective sectors of the Eurogreen model; 2) total expenditure per COICOP category is obtained from Eurostat; 3) total households' final expenditure per NACE sector from WIOD is converted to purchaser prices using Cazcarro et al. (2022) conversion factor, and re-scaled so that the total across sectors matches the total across COICOP categories from step (2); 4) the RAS algorithm is applied to the benchmark bridge matrix from (1), using values from (2) as column constraints and values from (3) as row constraints.

each period these expenditure shares per sector are adjusted for inflation: they respond to the change in the ratio of each sector's price to the overall price index, per region and quintile. These price ratios are computed using updated weights, and the relevant elasticities are computed regressing the observed expenditure shares in HBS over price series from Istat, for 2014 and 2017, and controlling for real expenditure. The resulting expenditure shares are then re-scaled proportionally to guarantee that they sum to one in each period. In this way, household consumption per sector evolves over time in response to variations in real income (coming both from the overall propensity to consume and changes in each expenditure share) and sector specific prices. Finally, consumption in purchaser prices is converted into consumption in basic prices, using the taxes less subsidies rates and trade and transport margins estimated by Cazcarro et al. (2022), so that trade and transport margins are applied to consumption in real terms, while taxes less subsidies are applied to consumption in nominal terms.

2.3 The energy module

The main feature of the energy module in Eurogreen is the integration of monetary and physical input-output structures, so that the flows of energy across the economy can be tracked and related to specific monetary flows. Data from the Physical Energy Flow Accounts (PEFA) and the Energy Balance from Eurostat is used to build supply and use tables of net energy, and to compute the shares of energy autoproduction per sector, the energy import shares by product, and to split the NACE D sector into the three subsectors considered in Eurogreen: electricity, gas and heat. An important assumption here is that the imported energy supply structure equals the domestic one, in other words, it is assumed that the intersectoral flows of energy required to produce abroad the energy imported is equal to that structure in Italy.

This data is then combined with monetary input-output tables from WIOD to build a monetary input-output table for energy. This table represents the monetary interindustry flows that are related to selling and buying of energy across sectors, so it allows to compute energy intensities and net energy use of inputs coming from the agricultural and mining sectors, since only a fraction of their sales of inputs to other sectors consists of energy transactions: biofuels in the case of agriculture, and fossil fuels for the mining sector. On the contrary, sales of inputs by petroleum refining and electricity, and autoproduction of energy by other sectors, are assumed to have an energy intensity equal to one.

The net energy supply and use tables allow to determine the own use of energy per sector, and to determine which sectors are net users or suppliers of energy. With this information, the energy intensities from the monetary energy input-output table are applied to the net energy supply and use table, and the RAS algorithm is applied with the row and column totals used as constraints to obtain the physical energy input-output table. Energy intensities and net use shares can then be applied to translate physical flows of energy into monetary ones in the model.

More precisely, let us define $\mathbf{M}$ as the $n \times n$ matrix of energy-related shares of monetary technical coefficients (with $n = 21$), derived from the monetary input-output table for energy. Each element of $\mathbf{M}$, $m_{ij} = a^E_{ij}/a_{ij}$, represents the energy purchases by sector j from sector i (a^E_{ij}) as a fraction of total purchases by sector j from sector i (a_{ij}), everything in monetary terms and per unit of output of sector j. On the other hand, matrix $\mathbf{E}$ is a $n \times n$ matrix of energy intensities, which allows the translation between physical and monetary flows of energy. Each element of $\mathbf{E}$ is defined as $e_{ij} = E_{ij}/z^e_{ij}$, so that this matrix captures the amount of energy in Terajoules per monetary unit of energy-related inter-industry trade.

Using the PEFA and Energy Balance datasets, inter-industry energy trade flows are split between 7 different energy sources.[6] Denoting by $\eta_{kij} = E_{\epsilon ij}/E_{ij}$, the share of the energy source ϵ in the total flow of energy of inter-industry trade from sector i to sector j (such that $\sum_\epsilon E_{\epsilon ij} = 1$), we obtain the total energy coming from energy source ϵ embedded in the interindustry flows from sector i to sector j, per unit of output of sector j:

$$a_{ij} \cdot m_{ij} \cdot e_{ij} \cdot \eta_{\epsilon ij} = a_{ij} \cdot \frac{a^e_{ij}}{a_{ij}} \cdot \frac{E_{ij}}{a^e_{ij} x_j} \cdot \frac{E_{\epsilon ij}}{E_{ij}} = \frac{E_{\epsilon ij}}{x_j} \tag{15}$$

Now, summing across the supplying sectors, we obtain the total amount of energy per unit of output of sector j coming from energy source ϵ:

$$\frac{\sum_i E_{\epsilon ij}}{x_j} = \frac{E_{\epsilon j}}{x_j} = \eta_{\epsilon j} \tag{16}$$

The same procedure is used to compute imported energy embedded in intermediate inputs per unit of output, since the PEFA, Energy Balance, and WIOD datasets allow to compute corresponding $\mathbf{M}^{imp}$ and $\mathbf{E}^{imp}$ matrices as well as $\eta^{imp}_{\epsilon ij}$ coefficients for imported inputs. The input-output structure of imported inputs is in turn defined in reference to the domestic one by applying import shares, $\mu_{ij} = a^{imp}_{ij}/a_{ij}$ to the technical coefficients:

$$\mu_{ij} \cdot a_{ij} \cdot m^{imp}_{ij} \cdot e^{imp}_{ij} \cdot \eta^{imp}_{\epsilon ij} = \frac{a^{imp}_{ij}}{a_{ij}} \cdot a_{ij} \cdot \frac{a^{imp,e}_{ij}}{a^{imp}_{ij}} \cdot \frac{E^{imp}_{ij}}{a^{imp,e}_{ij} x_j} \cdot \frac{E^{imp}_{\epsilon ij}}{E^{imp}_{ij}} = \frac{E_{\epsilon ij}}{x_j} \tag{17}$$

[6]The energy sources are: 1) Coal and coal products; 2) Natural gas; 3) Oil and petroleum products; 4) Nuclear fuel; 5) Biofuels; 6) Electricity; and 7) Heat. Renewable energy sources are not included here since they consist of the use of natural resources rather than trading those resources between sectors; this sources are included in the production of electricity and heat.

And

$$\frac{\sum_i E^{imp}_{\epsilon ij}}{x_j} = \frac{E^{imp}_{\epsilon j}}{x_j} = \eta^{imp}_{\epsilon j} \tag{18}$$

To compute emissions it is important to consider that not all transactions of energy products will result in emissions, since some of this products can be used for other purposes rather than fuels (for example, petroleum derivatives used as inputs to produce plastics) or can be used in energy transformation. The energy supply and use tables allow to compute coefficients for emissions-relevant energy use, which are denoted by $\varepsilon_{\epsilon j} = EE_{\epsilon j}/E_{\epsilon j}$, with $EE_{\epsilon j}$ denoting emissions-relevant energy use. Lastly, emissions factors are computed using data from the International Energy Agency for oil, coal and gas energy sources, and from ISPRA for biofuels, using also Eurostat to harmonize between the different residence criteria for emissions in the two datasets.[7] Denoting emission factors by $c_\epsilon = CO2_\epsilon/EE_\epsilon$, embedded emissions per unit of output of sector j can be computed as:

$$CO2_j = \sum_\epsilon c_\epsilon \varepsilon_{\epsilon j}(\eta_{\epsilon j} + \eta^{imp}_{\epsilon j}) \tag{19}$$

An analogous approach is used to compute direct emissions by households, using analogous $\mathbf{M}^C$, $\mathbf{M}^{C,imp}$, $\mathbf{E}^C$ and $\mathbf{E}^{C,imp}$ matrices. and $\eta^C_{\epsilon j}$, $\eta^{C,imp}_{\epsilon j}$ and $\varepsilon^C_{\epsilon j}$ coefficients for households final domestic and imported consumption. Let us define $m^C_j = C^e_j/C_j$, $e^C_j = E^C_j/C^e_j$, $\eta^C_{\epsilon j} = E^C_{\epsilon j}/E^C_j$ and $\varepsilon^C_{\epsilon j} = EE^C_{\epsilon j}/E^C_{\epsilon j}$, where C_j denotes total consumption of j sector by households and the superscript C denotes a coefficient computed for final household consumption. Then:

$$\frac{C_j}{x_j} \cdot m^C_j \cdot e^C_j \cdot \eta^C_{\epsilon j} = \frac{C_j}{x_j} \cdot \frac{C^e_j}{C_j} \cdot \frac{E^C_j}{C^e_j} \cdot \frac{E^C_{\epsilon j}}{E^C_j} = \frac{E^C_{\epsilon j}}{x_j} \tag{20}$$

And

$$\frac{C^{imp}_j}{x_j} \cdot m^{C,imp}_j \cdot e^{C,imp}_j \cdot \eta^{C,imp}_{\epsilon j} = \frac{C^{imp}_j}{x_j} \cdot \frac{C^{e,imp}_j}{C^{imp}_j} \cdot \frac{E^{C,imp}_j}{C^{e,imp}_j} \cdot \frac{E^{C,imp}_{\epsilon j}}{E^{C,imp}_j} = \frac{E^{C,imp}_{\epsilon j}}{x_j} \tag{21}$$

Direct emissions from households' final consumption per unit of output of sector j can

[7] Nuclear fuel, electricity and heat do not directly produce emissions.

thus be computed as:

$$CO2_j^C = \sum_{\epsilon} c_{\epsilon}\varepsilon_{\epsilon j}\left(\frac{E_{\epsilon j}^C}{x_j} + \frac{E_{\epsilon j}^{C,imp}}{x_j}\right) \tag{22}$$

Let us now denote by $\boldsymbol{\vartheta}$ and $\boldsymbol{\vartheta^C}$ the $(1 \times n)$ vectors of embedded ($CO2_j$) and direct ($CO2_j^C$) emissions per unit output respectively. Accordingly, denoting by $\mathbf{L}$ the Leontief inverse matrix, by $\boldsymbol{\mu}$ the matrix of import shares for intermediate inputs, and by $\mathbf{C}_{RQ}^{HH}$ the $(n \times 1)$ vector of final consumption for the representative household of region-quintile RQ, we can compute the consumption-based emissions for all household types in the model using standard enviornmentally-extended input-output techniques (Oswald et al., 2020).

$$CO2_{RQ}^{HH} = (\boldsymbol{\vartheta L} + \boldsymbol{\vartheta}(\boldsymbol{\mu} \circ \boldsymbol{L}) + \boldsymbol{\vartheta^C})\mathbf{C}_{RQ}^{HH} \tag{23}$$

Using the number of households per region and quintile, we compute the Gini index to measure carbon inequality across regions and quintiles. On the other hand, denoting by g and $\mathbf{i}$ the vectors of final demand from government consumption and investment, total consumption-based emissions from the country are computed as:

$$CO2^{CB} = (\boldsymbol{\vartheta L} + \boldsymbol{\vartheta}(\boldsymbol{\mu} \circ \boldsymbol{L}))(\mathrm{g} + \mathbf{i} + \mathbf{C}_{RQ}^{HH}) + \boldsymbol{\vartheta^C}\mathbf{C}_{RQ}^{HH} \tag{24}$$

2.4 Policies and scenarios

In this framework we simulate two policies that purport to reduce emissions through market mechanisms: a Carbon Tax and a faster reduction of emission permits in the EU Emissions Trading Scheme. We simulate a third policy by which these market mechanisms are used to reduce inequality: a redistribution of carbon-related government revenues to population in a progressive way. We refer to these policies as *CT*, *ETS* and *Redistribution* respectively.

Using emissions per unit of output as described above, unit carbon costs of sector j are $ucc_j = ucc_j^{CT} + ucc_j^{ETS}$. We assume that carbon costs are fully passed on to consumers, and are included in the taxes-less-subsidies (tls) component of purchaser prices. Initial values for tls rates are taken from Cazcarro et al. (2022), and unit carbon costs are added on top of them each period. The vector of final embedded carbon costs per unit of output in basic prices is given by $\boldsymbol{fcc_j} = \boldsymbol{uccL} + \boldsymbol{ucc}(\boldsymbol{\mu} \circ \boldsymbol{L})$. The second summand arises due to our assumption that other trade partners also implement an equivalent carbon price, since Italy's main trading partners are other EU countries. There is thus a discrepancy between carbon costs paid by consumers through prices and carbon revenues for the domestic government, which are only $\boldsymbol{uccL}$. On the other hand, we also assume that households pay the carbon tax on their directly produced emissions. We use unit direct emissions from households' consumption as described above, and multiply it by the consumption vector and the carbon tax rate per each region and quintile, $ucc^D_{RQ} = \boldsymbol{\vartheta}^{\boldsymbol{C}} \mathbf{C}^{HH}_{RQ} \tau^{CT}$. Total carbon revenues for the government is thus $cr = \boldsymbol{uccLf} + \boldsymbol{\vartheta}^{\boldsymbol{C}} \mathbf{C} \tau^{CT}$, with $\boldsymbol{f}$ and $\mathbf{C}$ denoting the vectors of total final demand and total households' consumption.

Carbon costs derived from ETS policies follow the functioning of the EU Emissions Trading Scheme (ISPRA, 2021). That scheme targets certain sectors that in the Eurogreen model correspond mainly to Mining, Manufacturing, Refining of petroleum, Electricity, Heat, Transport and Water. However, not all producers in these sectors are required to participate in the trading scheme, so we use the ratio of verified emissions in ETS to total emissions to compute the shares of each sector participating in the scheme. Using this shares, we split total sector emissions between those subject to carbon tax costs and those subject to ETS costs (we assume that units participating in ETS do not pay the carbon tax). The ETS system works in the following way: each period there is a total number of emission allowances, which sets the cap of overall emissions for these industries as a whole, and a number of freely allocated allowances to each sector. At the end of the period firms must surrender a number of allowances at least equal to their emissions. Sectors in deficit (a number of allowances lower than emissions) can buy allowances from the government in auctions paying a price, and they must pay a penalty if they fail to surrender the required amount of allowances. These are the two components of the ETS-related carbon cost in Eurogreen, ucc^{ETS}_j. Data for modeling the ETS system in Eurogreen is taken from the European Environment Agency (EEA).

Finally, we simulate the redistribution policy as a transfer from the government to households of the total amount of carbon revenue cr. These transfers are allocated individuals below a certain annual income threshold. Denoting by $\tilde{N}^k_{s,g,RQ}$ the number of eligible persons for the redistribution policy per region-quintile, this money is allocated on a per-capita basis, such that carbon-tax-redistribution for region-quintile RQ is:

$$Y^{Red}_{RQ} = \frac{cr}{\sum_{k,s,g} \tilde{N}^k_{s,g,RQ}} \tag{25}$$

Accordingly, the disposable income of each household will be affected by the direct carbon costs paid (carbon tax on direct emissions) and the transfers of the redistribution policy. Net carbon income for household of region-quintile RQ is thus defined as:

$$CY_{RQ} = numHH_{RQ} \left[Y^{Red}_{RQ} \sum_{k,s,g} (\pi^k_{s,g,RQ} N^k_{s,g,RQ}) - ucc^D_{RQ} \right] \tag{26}$$

The carbon tax rate in the baseline is set at 0, and in the CT scenario it is set at 50€ per ton of CO2, increasing linearly until 200€ in 2050. For the ETS system, the number of emission allowances both total and freely allocated across sectors, are taken from historic

EEA data, free allowances are set to arrive at 0 in 2030, total allowances reduce at an annual rate of 2.2%, auction prices are taken from historic data from EEA and extrapolated onwards, and ET penalties are set at 100€ per ton of CO2. These parameters for the baseline are set accordingly with current EU regulation, while in the ETS scenario the annual reduction rate of total allowances is set at 15%. Finally, we assume that those eligible for carbon redistribution transfers are the working-age individuals with an annual income lower than 15.000€.

3 Results

The different scenarios are simulated using 2010 as base year and a time-span of 40 years, so that the end period is 2050. All policies are simulated to start in 2022, and the model includes demand and activity shocks in 2019 due to the pandemic, and price shocks in 2022 due to energy prices. A first indicator to consider is consumption-based emissions for the whole country.[8] It can be seen in figure 1 that there is a decreasing trend after 2030, which mainly responds to resource-saving technical change. This pattern do not differ across scenarios, but all the alternative scenarios exhibit lower emissions with respect to the baseline. The most effective policy in this respect is the carbon tax, although in a longer time-span the combination of carbon tax and more stringent ETS regulations produces higher emissions reductions. The carbon costs redistribution policies towards lower income persons, in turn, implies higher emissions but it still achieves considerable reductions in the long-term.

A second indicator is carbon inequality across households, depicted in figure 2. It can be seen that carbon policies alone do not have a great impact in terms of carbon inequality with respect to the baseline, although in the longer run they seem to increase carbon inequality slightly. Carbon costs redistribution, on the contrary, helps to strongly reduce carbon inequality, although it does not change too much the trend observed in other scenarios. This pattern is also observed for income inequality, as shown in figure 3.

These results show that there is a trade-off between environmental goals, reflected in reduction of greenhouse gases, and social goals, reflected in the reduction of inequality, both in terms of income and carbon emissions. This is evident when looking at the long-run trends of both types of indicators, as the time period of emissions reductions coincide with an increase in inequality, while growing emissions are associated with falling inequality. However, we also find that policies for emission reductions can be repurposed to also achieve social goals, with losses in terms of emissions reduction that are relatively lower than gains in terms of lower inequality.

[8] It is important to note that the emissions are lower than other estimations for Italy from the Global Carbon Project, for example. This is due to two assumptions of the model: first, the energy input-output structures for domestic and imported production are considered to be the same, while in practice the imported one is more energy intensive; second, we consider only energy-related emissions, so leaving aside other sources of emissions like land-use change.

Figure 1: Consumption-based emissions

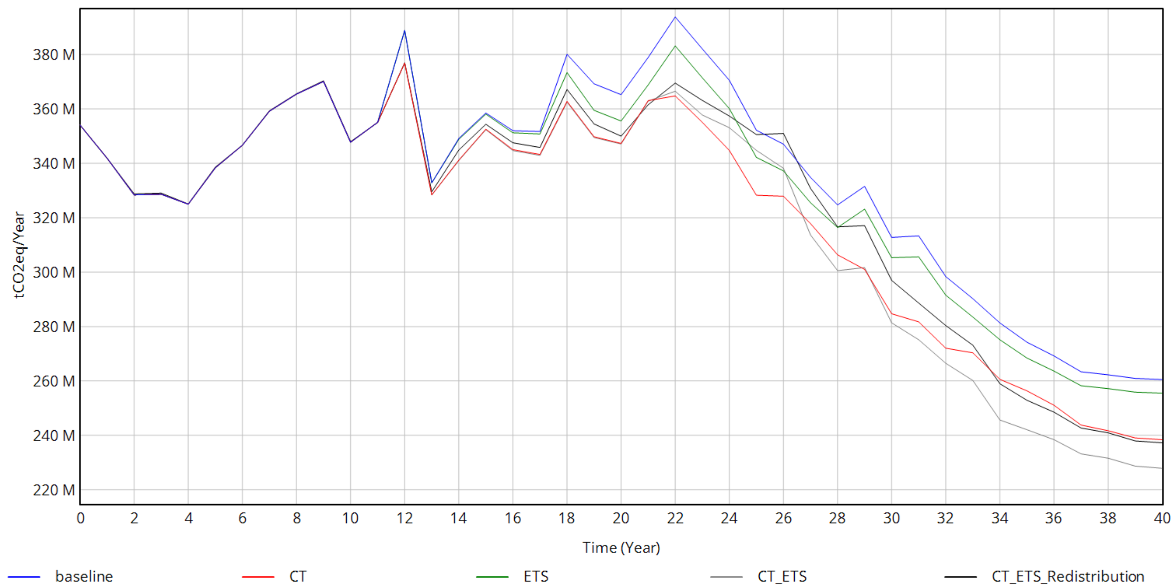

Figure 2: Gini index for households' emissions

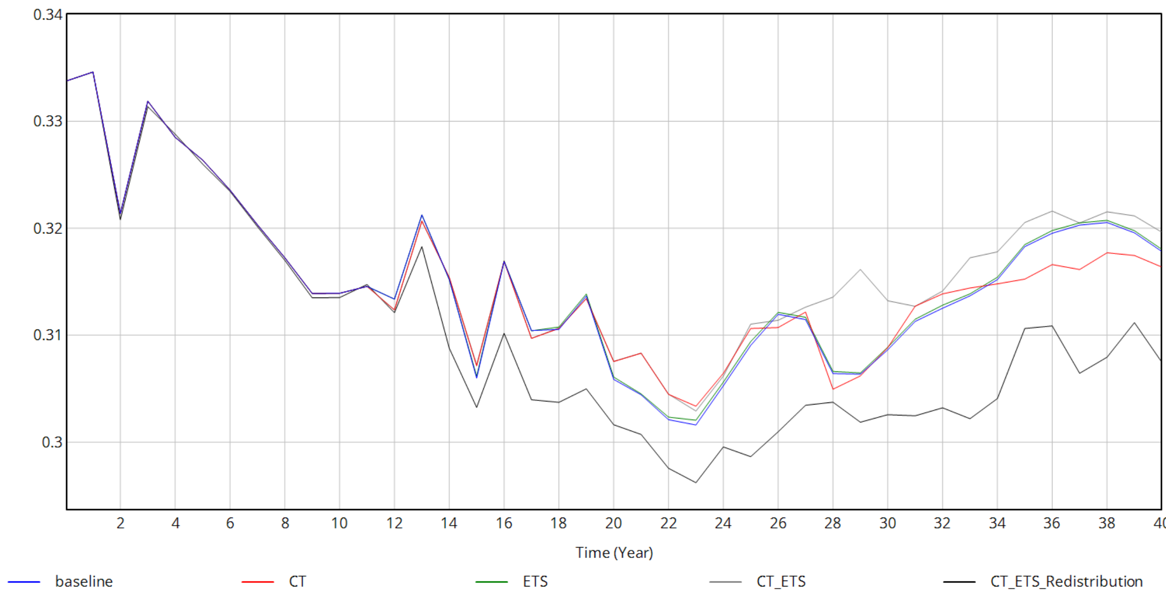

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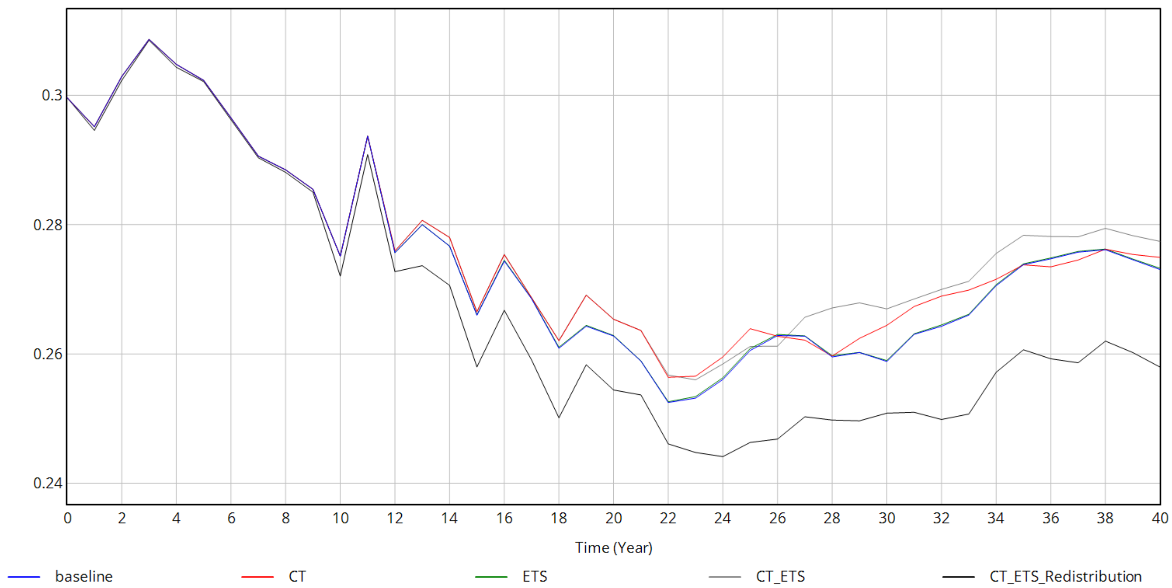
Figure 3: Gini index for households' disposable income



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