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Nicola Campigotto, Marco Catola, Andrè Cieplinksi, Simone D'Alessandro, Tiziano Distefano, Pietro Guarnieri, Till Heydenreich

Scenario discovery for a just low-carbon transition

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Discussion paper

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Keywords: ecological macroeconomics; just transition; inequality; scenario discovery

JEL CLassification: Q56; Q57; C63

Scenario discovery for a just low-carbon transition

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Abstract

There is currently no consensus among scholars on how to achieve a just low-carbon transition. To address this issue, this paper subjects a macrosimulation model to an extensive sensitivity analysis and then fits random forests to the simulation results to identify policy combinations that can reduce carbon emissions while promoting income equality. Our findings indicate that interventions aimed at supporting low-income groups result in an increase in these groups' energy demand and emissions, and that this negative effect should be offset through a faster deployment of renewable energy sources and measures that redistribute income away from top earners. Our analysis also confirms the importance of well-known policies such as carbon taxation and working time reduction. On the other hand, we do not find energy efficiency to be crucial in achieving inequality and emission reduction goals.

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1 Introduction

Seldom before have concerns about the environment and inequality been so closely related. Evidence from surveys conducted around the world indicates that inequality and climate change are frequently identified as among the most pressing issues of our day (see e.g. European Parliament 2019; Bowles and Carlin 2020), and public and scholarly debates abound on the kinds of measures necessary to secure people's livelihoods in the transition away from fossil fuels. These challenges are often framed within the concept of a 'just transition', which calls for action at the international, national and local levels to ensure a fair and equitable transition for all individuals (McCauley and Heffron 2018; O'Neill et al. 2018; Fanning et al. 2020; Millward-Hopkins and Oswald 2021). A related principle has become central to the way some policymakers conceive climate interventions. In late 2019, European Commission's President Ursula von der Leyen presented the European Green Deal as 'a strategy for growth that gives more back than it takes away', stressing that 'we have to be sure that no one is left behind [...] this transition will either be working for all and be just or it will not work at all' (European Commission 2019).

The need for tools to understand and guide the transition to sustainability has given impetus to the emerging field of ecological macroeconomics (henceforth EM; Rezai and Stagl 2016). The models developed in this literature typically feature a range of economy-environment interactions, energy use, and disaggregated production and consumption (Barker et al. 2016; Dafermos et al. 2017). Moreover, consistent with empirical evidence (Haberl et al. 2020), they share a general skepticism about the possibility of rapidly achieving an absolute decoupling of economic activity from environmental pressures.

It is perhaps surprising, however, that despite burgeoning advocacy for just transition efforts, EM has paid relatively little attention to how to jointly meet low-carbon and distributive goals. Research in this area tends to focus on the energy-environment-growth nexus, while inequality and other aspects of well-being receive considerably less attention (Hardt and O'Neill 2017). Often the income distribution is considered only in functional terms (that is in terms of profit and wage shares, e.g. Jackson and Victor 2016; Dafermos et al. 2017), which makes it difficult to thoroughly assess inequality. Inevitably this modelling stance influences the kinds of policies EM seeks to examine: as detailed in Section 2, most studies are concerned with direct climate mitigation measures, whereas those investigating the impact of socioeconomic policies are considerably fewer in number.

A different but related point is that the standard approach in EM is to consider pre-conceived scenarios featuring a small number of policies. This approach consists in choosing one or more (usually two) policy measures that are deemed relevant to the context being studied, translating them into suitable input parameters, and simulating the resulting dynamics. As a consequence, on one hand, research ends up being guided by *a priori* prescriptions on how to address social and environmental challenges; on the other, a large portion of the policy space is left unexamined.

This paper proceeds in the opposite direction, taking a scenario discovery perspective (Lempert et al. 2006; Groves and Lempert 2007) to explore interventions for a low-carbon, low-inequality transition. We introduce a revised version of the Eurogreen macrosimulation model (D'Alessandro et al. 2020) and use data from about 16,000 simulation runs to identify policy combinations that address distributive and climate challenges. Our findings and recommendations are the result of an ex-post assessment. First, the model is repeatedly run within the parameter space. In each simulation, more than one hundred parameters are randomly drawn from a wide range of possible values. Second, random forests are used on the database of simulation results to understand which parameter combinations can simultaneously improve social, economic and environmental indicators. Finally, successful combinations are interpreted either as policy prescriptions or modelling choices. The paper addresses questions such as: what policy combinations, if any, make decarbonisation and inequality reduction compatible? Does the pursuit of growth affect the set of policies available for achieving a just low-carbon transition? Has the literature overlooked relevant policy alternatives or overemphasized others?

The results indicate that the achievement of low-carbon-and-inequality goals can benefit from interventions targeted at both ends of the income distribution, which however have different effects on growth and emissions. Policies supporting bottom income groups do certainly play a role in addressing inequality, but the consequent increase in these groups' demand for goods and energy calls for stronger environmental policies to cut emissions. Conversely, measures that redistribute income away from high earners can make the income distribution more equal while balancing changes in energy consumption and emissions across income groups. Our findings further suggest that although a just low-carbon transition neither prevents nor requires sizeable GDP growth, the primacy of economic growth as a policy objective makes the path towards a just transition narrower, that is it reduces the range of feasible policy combinations.

The remainder of the paper is organised as follows. Section 2 presents some stylised facts about the use of scenarios in EM. Section 3 describes the main features and novelties of the Eurogreen model, and then introduces our scenario discovery approach. Section 4 discusses the main results and their policy implications. Section 5 concludes and suggests avenues for further research.

2 Scenarios and policies in ecological macroeconomics

To place our work in perspective, we conducted a systematic review of the use of scenarios in the EM literature. We limited the analysis to this specific research area to improve comparability with the model presented in this paper. The term 'scenario' denotes a consistent, model-based description of how the future may evolve under a certain set of input assumptions. Different scenarios result from alternative assumptions, which in turn reflect different policies or hypotheses about socio-economic and environmental conditions (Moss et al. 2010). The full list of articles and scenarios is available for download at Zenodo (see Code availability section below).

All publications dated 2010 or later and retrieved by posing the query ‘ecological macroeconomics’ in Scopus (34 results) and Web of Science (33 results) were initially considered for analysis. Additionally, we considered the 44 publications included in the literature review by Hafner et al. (2020, Table 2). After discarding duplicates from the three sources, we were left with 87 publications. The sample was then restricted to articles featuring scenarios and published in peer-reviewed journals. This reduced the number of publications to 25.

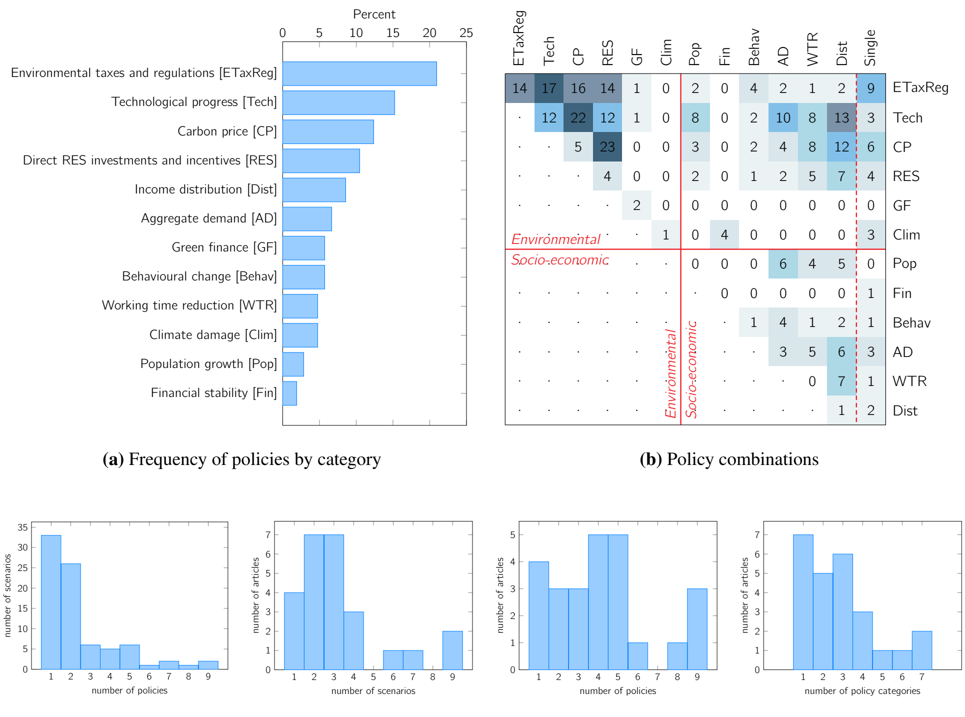
The next step was to determine how many scenarios were simulated in each article and what policies comprised each scenario. To do so, we went through all articles and identified all input parameters that varied across simulations. Often these exogenous parameter changes are framed as hypotheses rather than policy measures. This is the case, for instance, for variations in the pace of technological progress, changes in the wage and profit shares of income, and higher or lower projections of emissions and temperature increases. We made no explicit distinction between policies and hypotheses, as we understand that both are equally important in allowing articles to make their points. Moreover, whether a model can incorporate well-defined, real-world policies rather than general hypotheses depends on its level of abstraction and geographical coverage. For brevity, hereafter we use the term ‘policies’ to refer to both actual policies and hypotheses.

The review led to the identification of 199 scenarios and 105 policies. The latter were finally grouped into 12 environmental and socio-economic categories (see Figures 1a and 1b for the complete list of policy groups and for how groups were classified as environmental or socio-economic). The classification process was largely based on the frequency with which similar policies appeared in the literature. Some groups, such as *Carbon price* and *Working time reduction*, are narrow in scope, as the policies that belong to them were observed frequently and implemented in similar ways for simulation; the former comprises carbon taxes, cap-and-trade schemes (such as the EU-ETS) and border carbon adjustments.

Other groups consist of several related policies. We briefly describe them in turn. The *Direct RES investments and incentives* group mainly includes variations in the share of renewable energy sources (RES) in total energy use; feed-in tariffs for wind and solar energy were also grouped in this category. The *Environmental taxes and regulations* group comprises all kinds of environmental taxes and regulations, excluding those included in the Carbon price and Direct RES investments groups. Examples include regulations to prevent the construction of new coal plants, material input taxes, taxes on the consumption of carbon-intensive goods, and subsidies for green capital. The *Technological progress* group is composed of changes in energy and fuel efficiency, input-output technical coefficients, labour productivity, and R&D investments.

The *Income distribution* group includes changes in the functional income distribution, basic income, job guarantee, and rebates to households from carbon tax revenues. *Aggregate demand* policies encompass direct variations in aggregate demand components, such as pro- or counter-cyclical government spending. Finally, the *Behavioural change* group comprises all changes in agents' behaviour, including voluntary reductions in private consumption and network and snob effects in agent-based models; by definition these are not actual policies, although they may depend indirectly on policy measures such as information campaigns on climate change or energy efficiency improvements in household appliances.

Policies in the remaining categories — *Population growth*, *Climate damage*, *Green finance* and *Financial Stability* — were observed sporadically, but were considered too different from other policy measures to be grouped together with them. The *Climate damage* group consists of alternative hypotheses about the functional form of the climate damage function (e.g. quadratic rather than linear) and the likelihood of extreme climate events. The *Green finance* group includes reductions in interest rates and various forms of credit rationing influencing investment in green capital. The *Financial stability* group is comprised of bailout measures and other policies to sustain the financial system in face of increased climate risks.



(a) Frequency of policies by category

(b) Policy combinations

(c) Policies per scenario

(d) Scenarios per article

(e) Policies per article

(f) Policy categories per article

Figure 1: Summary of literature review

Figure 1a shows the frequency of the 12 policy categories. About 70 percent of policies consisted of environmental measures. Of these, 21 percent belonged to the Environmental taxes and regulations group, 15.2 percent to the Technological progress group, 12.4 percent to the Carbon price group, and 10.5 percent to the Direct RES investments group. Socio-economic policies add up to the remaining 30 percent of the total, with Income distribution, Aggregate demand, and Behavioural change being the most common groups (8.6, 6.7 and 5.7 percent, respectively).

Figure 1b was constructed by considering pairwise combinations of policy types. Each unique policy type combination featured in a given scenario adds 1 to the corresponding cell in the matrix. For example, a scenario consisting of a single Carbon price policy adds 1 to the (Single, CP) cell; a scenario with one Carbon price and one Income distribution policies adds 1 to the (Dist, CP) cell; a three-policy scenario featuring two different Carbon price policies and one RES policy adds 1 to the (CP, CP) cell and 2 to the (CP, RES) cell. The figure shows that most policy mixes combined policy instruments from the Environmental taxes and regulations, Technological change, Carbon price, and Direct RES investments groups. Socio-economic interventions were most often observed together with Carbon price and Technological progress policies; this is so particularly in the case of Aggregate demand, Working time reduction, and Income distribution.

The four bottom-row panels of Figure 1 provide summary information about the number of policies per scenario and the numbers of scenarios, policies and policy categories per article. About 60 percent of scenarios featured either 1 or 2 policies (Figure 1c), with the mean number of policies per scenario being 2.43. On average, articles included 3.28 scenarios and examined 4.20 policies from 2.88 policy groups. Eighteen out of 25 articles considered 3 or less scenarios (Figure 1d) and 3 or less policy categories (Figure 1f), and all except five articles considered 5 or less policies (Figure 1e). Overall, these findings seem to indicate that a gap exists between the positive and policy aspects of ecological macroeconomics. On one hand, research in this field seeks to investigate the complex relation between social, economic and environmental sustainability. On the other hand, however, scholars tend to rely on scenarios featuring a small number of policies, which are hardly suitable for the analysis of multidimensional policy objectives. This point is further discussed in Sections 3.2 and 5.

3 Methods

3.1 The model

The Eurogreen model is based on Post-Keynesian economic theory and combines system dynamics and stock-flow consistent methods. It is formulated at the country level and has previously been applied to France (D'Alessandro et al. 2020; Cieplinski et al. 2021a) and Italy (Cieplinski et al. 2021b). The simulations presented in this study were obtained for Italy and run from 2010 to 2050, while calibration is based on data for the period 2010-2020. Exogenous shocks to private consumption, investment, exports and imports were included to account for the Covid-19 pandemic. This section outlines the model structure, with emphasis on the new features introduced in this version. For a comprehensive discussion, see the supplementary material.

Aggregate demand drives production and consists of exports and government spending (which are mainly governed by exogenous trends), consumer spending, and gross fixed capital formation.

Households' consumption depends on disposable income, income-dependent marginal propensities to consume, and prices. Consumption is allocated among 16 different goods[1] as a function of relative price changes, with elasticities ranging from 0 to 1.5. Disposable income is determined by government transfers (such as unemployment benefits and pensions), labour and financial income, social security contributions, and income taxes. These variables differ by skill, gender and employment status (employed, unemployed, out of labour force, and retired, with the top 1 percent of individuals designated as capitalists or rentiers who only earn financial income). The new version of the model incorporates gender differences among agents, leading to a total of 25 different population groups and allowing for a thorough analysis of distributional issues. Moreover, since consumers' behaviour depends on income and prices, the model captures the feedback effects that arise from distributional and price changes, which in turn may result from such causes as technological progress, wage increases, or the introduction of a carbon tax.

Employment varies by skill and gender, and is determined as a function of labour productivity at the industry level, previous-period output, and weekly work hours. The skill composition of labour demand reflects industry-specific historical trends, whereas the gender composition depends on the difference between female and male unemployment rates within each skill group. Pensions and unemployment benefits are paid in proportion to wages, which in turn are affected by labour productivity, inflation, and group-specific employment rates. Financial income is made up of dividends on equity and interests on government bonds.

[1] Categorised according to the Classification of Individual Consumption According to Purpose (COICOP) scheme.

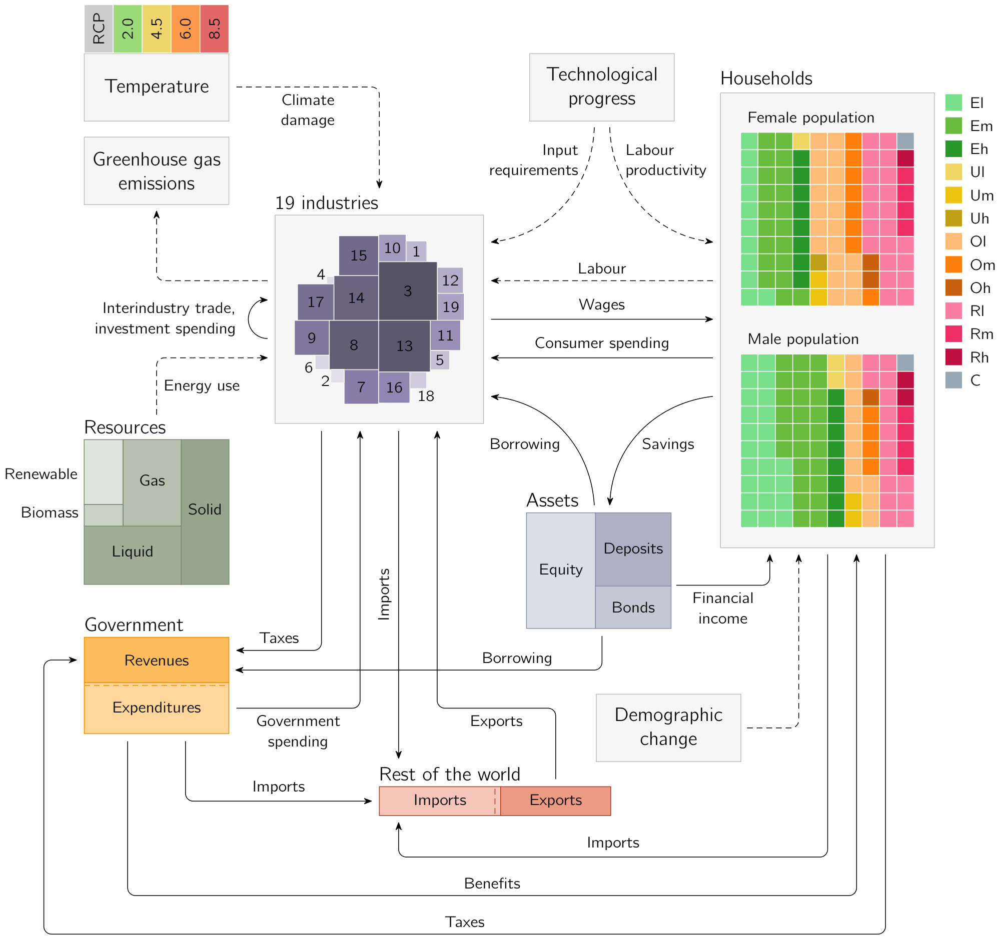


Figure 2: Model overview. The solid and dashed arrows represent monetary and non-monetary flows, respectively. The Households, Industries, Resources, Assets, Government, and Rest of the world boxes summarily represent first-period simulation results. The dashed lines in the Government and Rest of the world boxes are drawn for reference and cut the area of the rectangles in half. Abbreviations in the Households box describe the following groups: E = employed; U = unemployed; O = out of labour force; R = retired; l = low-skilled; m = middle-skilled; h = high-skilled; C = capitalists. List of industries: 1 = Agriculture, forestry and fishing; 2 = Mining and quarrying; 3 = Manufacturing; 4 = Coke and refined petroleum products; 5 = Electricity, gas and steam; 6 = Water supply; 7 = Construction; 8 = Wholesale and retail trade; 9 = Transportation and storage; 10 = Accommodation and food service activities; 11 = Information and communication; 12 = Financial and insurance activities; 13 = Real estate activities; 14 = Professional, scientific, technical, administrative and support service activities; 15 = Public administration and defence; 16 = Education; 17 = Human health and social work activities; 18 = Arts, entertainment and recreation; 19 = Other.

Industries adjust their desired investment on the basis of the difference between actual and normal capacity utilisation, striving to produce at the normal rate of capacity utilisation. However, investment spending is constrained by profits after debt repayment and taxes, which determine the maximum investment that each industry is able to finance. Another novel feature of this version of the model is that financing conditions are negatively affected by industry leverage.

Output is obtained by multiplying domestic final demand by the Leontief inverse matrix, and is constrained by fixed capital and capital productivity. Input-output technical coefficients change endogenously over time with technological progress. The innovation process can be summarised as follows. In each period, one or more new technologies can be discovered with a certain probability. Innovations may be labour-saving, intermediate-input-saving, or both. The probability that a new technology is discovered depends on labour and intermediate input costs; for example, if in a certain industry the unit cost of intermediate inputs increases relative to the unit cost of labour, then firms become less likely to develop new labour-saving technologies than new intermediate-input-saving technologies. Once a technology is discovered, the extent of technological progress in each industry is randomly determined from normal distributions calibrated to historical data. Finally, in each industry a choice is made (based on cost minimisation criteria) about whether to adopt a new technology and, if so, which one. This version of the model allows for improvements in production efficiency even in the absence of new innovations, due to the progressive diffusion of the newest available technology.

Technological progress also affects energy demand by increasing energy efficiency. Energy flows are linked to real domestic monetary flows, with energy demand to output coefficients specific to every industry-to-industry cell of the input-output matrix, and industry-specific coefficients for household consumption. Energy demand is met by five energy sources (solid, liquid, gas, biomass and renewables) according to industry- and household-specific shares, which change in time according to the projections of MISE-MATTM-MIT (2019). Greenhouse gas emissions are then determined, once again, using industry- and household-specific energy-source-to-emissions conversion coefficients. This approach allows energy demand and emissions to respond to changes in both the amount and composition of inputs required for production.

This new version also includes a climate damage function, defined as the fraction by which production varies relative to what it would be in the absence of global warming. Temperature projections are exogenous and based on Representative Concentration Pathways (RCPs). The functional form of climate damage draws on Desmet and Rossi-Hansberg (2015), with modifications to account for extreme climate events. In each period, industry-specific damages are drawn from a beta distribution and deducted from output, which is equivalent to an increase in intermediate input requirements.

The Government collects social security contributions, value added taxes, carbon taxes (if levied), and taxes on labour, financial and corporate income. It also makes transfers to households and purchases goods and services. Prices are determined as a markup over unit production costs. The population dynamic is exogenous and depends on demographic projections.

Although this version of the model addresses several shortcomings of the original version (such as the inclusion of a damage function, price elasticities of consumption demand, the introduction of leverage as a determinant of financing capacity, and a direct correspondence between inter-industry trade and energy demand), other limitations remain. The share of energy demand met by renewable sources is driven by an exogenous trends based on the growth rates that achieve national targets (MISE-MATTM-MIT 2019). Total energy demand depends directly on output and, therefore, on the level overall level of economic activity and on changes in technical coefficients; however, there is no direct feedback from the expansion of renewable sources to other socio-economic variables in the model.

The results are also influenced by the level of aggregation of industries and individuals. This is most relevant for income and carbon taxes. The lack of within-group variability in income results in a very limited number of individuals whose income falls in the highest and second-highest tax rate brackets. The homogeneity of emissions within industries also reduces the capacity of a carbon tax capacity to incentive renewable energy adoption among the most polluting plants in an industry. Moreover, homogeneous groups of income earners tend to reduce inequality due to a lower dispersion of income on the top end of the distribution. Finally, the model does not include non-energetic resources (such as water, land and raw materials) and does not consider how the use of natural resources might impact the local ecological processes (e.g. biodiversity loss, water pollution).

3.2 Simulation and data analysis approach

The use of scenarios in macrosimulation models provides an intuitive and appealing way to envision plausible futures and evaluate policy alternatives in contexts of deep uncertainty. As shown in Section 2, a common practice in the literature is to construct ex-ante a limited number of alternative scenarios, each featuring a different combination of input parameters, and frame them as possible states of the world. However, this approach is complicated by issues concerning the choice of how scenarios are constructed, which strongly relies on the modellers' prior knowledge about the phenomena being examined and the main causal relations among the model variables.

An alternative strategy, which we adopt in this study, is to identify relevant scenarios that emerge spontaneously from a database of simulations (Lempert et al. 2006; Groves and Lempert 2007; Gerst et al. 2013; Guivarch et al. 2016). This approach requires running the model a large number of times, each time with a new set of inputs randomly drawn from the parameter space. The database of simulation outcomes is then partitioned into regions according to a pre-defined criterion, and statistical learning methods are used to determine which parameters best predict the simulations' position in the partitioned outcome space.

The data used in our analysis were obtained by running the Eurogreen model 50,000 times. In each simulation run, the value of 107 different parameters was selected at random from a given distribution. The list of parameters and their respective distributions are given in Appendix C, while a detailed discussion of the role of each parameter is provided in the supplementary material. Some parameters, named 'structural parameters', can take only integer values corresponding to different economic or environmental assumptions. For instance, the *Warming scenarios* parameter can take values ranging from 1 to 4, each corresponding to a different Representative Concentration Pathway and temperature projection. The *Carbon tax* parameter takes value 1 if emissions are taxed (starting in 2022), and 0 otherwise. The *Output constraint* parameter indicates whether production capacity is constrained by fixed capital (value 0) or not (value 1). The *Investment constraint* parameter takes a value of 0 if no restriction is placed on firms' investment, a value of 1 if firms must internally finance a fixed proportion of their investment expenditures, and a value of 2 if this proportion depends on leverage.

Other parameters, named 'non-calibration parameters', can vary over a wide range of values, which generally spans from -50 to $+50$ percent of the parameter's initial value. This group includes, among others, the depreciation rate of fixed capital, the number of working hours per year, the pension-to-wage and unemployment benefits-to-wage ratios, and several tax rates. Each non-calibration parameter follows a linear trend, starting from a given initial value in 2022 and reaching the randomly selected value in the final simulation year (2050). For example, if a value of 0.25 is drawn for the *Value added tax (VAT) rate* parameter, then the VAT rate will remain constant from 2010 to 2022 and then progressively increase in a linear fashion, ultimately exceeding its initial level by 25 percent by the end of the simulation run.

Finally, the 'calibration parameters' group mainly comprises the parameters for which the model was calibrated. Since calibration was performed to fit observed data, these parameters usually span a smaller range of values than non-calibration parameters. Moreover, their value is randomly drawn in the first period and then remains constant throughout the simulation run. Examples include the sensitivity of wages and consumption to price changes, and the percentage of profits paid out as dividends.

Although most parameters can easily be understood in policy terms, there are also some parameters which are beyond the direct control of policies. The latter usually reflect different, alternative modelling assumptions. For example, changes in the *output constraint* parameter can help understand the consequences of letting output be constrained by the capital stock. Thus, our work speaks to both the policymaking and EM modelling literatures.

Out of the 50,000 simulations, only 16,023 were deemed suitable for analysis. We stress that this is not a cause for concern. Since the output of each run depends on the joint realisation of many random variables, it can well be the case that a combination of several high- or low-valued parameters is drawn as input data, leading to economically implausible results. This point is substantiated by the kernel density estimates presented in Appendix A, which show that the share of simulations suitable for analysis and which featured extreme-valued parameters is small. The most common reasons for dropping simulations were a negative or very high (300 percent or more) debt-to-GDP ratio (about 24 and 9 percent of dropped simulations, respectively) and a negative unemployment rate of male and female low, middle, or high-skilled workers (37 percent, 7 percent and 22 percent, respectively).[2]

The simulations were grouped into mutually exclusive classes according to four different criteria, each reflecting a policy objective: (1) reducing greenhouse gas emissions; (2) reducing income inequality (measured by the Gini coefficient of net income); (3) reducing emissions and inequality; (4) reducing emissions and inequality while increasing GDP. We refer to these as the GHG, Gini, GHG-Gini, and GHG-Gini-GDP objectives, respectively. In the GHG case, simulations were grouped into a 'high GHG' or 'low GHG' class depending on whether the level of emissions in the final simulation period was above or below the last-period median value. Similarly, in the Gini case, simulations were grouped into a 'high Gini' or 'low Gini' class. In the GHG-Gini case, the classification was based on two different thresholds resulting in four classes: 'high GHG, high Gini', 'high GHG, low Gini', 'low GHG, high Gini', and 'low GHG, low Gini'. Finally, in the GHG-Gini-GDP case, simulations were grouped into eight different classes: 'high GHG, high Gini, high GDP', 'high GHG, high Gini, low GDP', . . ., 'low GHG, low Gini, low GDP'.

For each policy objective, we trained a random forest that predicts the outcome of simulations. To do so, we first split the data into a training set (70 percent of simulations) and a test set (30 percent) using stratified sampling. In the GHG-Gini and GHG-Gini-GDP cases, due to moderate imbalances in the class distribution of simulations, we also used a combination of majority class undersampling and synthetic minority class oversampling of the training data to improve the sensitivity of under-represented classes. Appendix B provides a description of the resampling procedure and shows that our results are robust to alternative resampling methods.

Random forests combine the results of many classification trees, each based on a bootstrapped subset of the training data. A classification tree is grown by partitioning the space of

[2]This results from an incompatibility between the randomly drawn input values determining the gender and skill distribution of labour demand (e.g. *Investment sensitivity*, *Technologies probability sensitivity*; see Appendix C), and those contributing to variations in the labour force participation rate (*Labour force participation sensitivity*), the substitution between male and female workers of the same skill level (*Gender employment substitution sensitivity*), and skill transitions (*Skill transition sensitivity*).

input parameters using a recursive binary splitting algorithm, so as to predict which outcome class each simulation belongs to (Breiman et al. 1984). Initially, at the top of the tree, all simulations belong to a single region. The algorithm then repeatedly splits the data into increasingly homogeneous regions. Each split is made according to a specific cut-point value of a selected input parameter. Simulations in a region are subdivided in two regions based on whether or not their value of the selected parameter exceeds the parameter's cut-point value. The parameter and its cut-point value are chosen to minimise the classification error rate, i.e. the fraction of observations in a region that do not belong to the region's most common outcome class. At each step of the splitting procedure, a different random subset of input parameters is drawn as split candidates. Following standard practice, the number of split candidates was chosen to approximate the square root of the total number of parameters (James et al. 2021); that is, at each new split in the tree a random sample of 10 parameters was drawn as split candidates from the full set of 107 parameters.

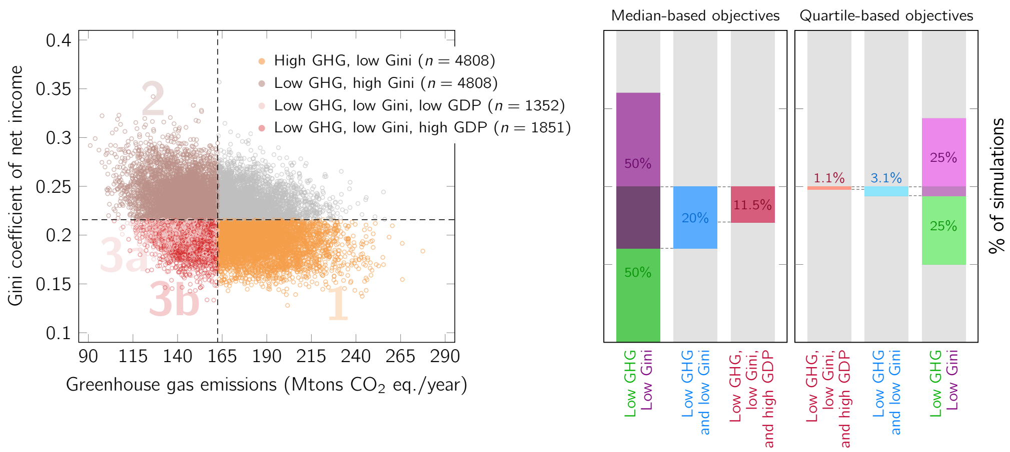
The prediction of each random forest was obtained by averaging the predictions of 500 classification trees. In the GHG and Gini cases, the random forest correctly predicted the outcome of more than 83 and 81 percent of simulations, respectively, whereas the GHG-Gini model had a 65 percent accuracy rate. In the GHG-Gini-GDP case, prediction accuracy decreased to about 53 percent, which is modest but in line with other studies on multi-objective scenario discovery (e.g. Gerst et al. 2013).

The predictive value of input parameters was evaluated based on their permutation feature importance, which is a measure of the decrease in the performance of the random forest when the values of a parameter are randomly shuffled (Breiman 2001; Strobl et al. 2008). The shuffling procedure breaks the relation between the parameter and the outcome variable, and the resulting variation in model performance is indicative of the extent to which predictions depend on that parameter. A high permutation feature importance denotes an important predictor of the simulation outcome.

4 Results

4.1 The emissions-inequality-GDP nexus

Before considering which parameter values are compatible with the simultaneous curtailment of emissions and inequality, it is useful to assess the likelihood of achieving both goals simultaneously. Figure 3a plots greenhouse gas emissions and the Gini coefficient of net income for all simulations in the final year 2050. Starting from the same position in 2010, different parameter combinations can drive the economy to a variety of outcomes. The Gini coefficient ranges from 0.13 to 0.30, starting from an initial value of 0.23; greenhouse gas emissions fall between 50 and 85 percent relative to their initial value of more than 500 Mtons CO_2 eq./year; real GDP ranges between 1.25 and 2.25 trillion euros, starting from an initial level of 1.46 trillion, meaning that the GDP growth rate ranges from slightly negative to moderately positive values.[3]



(a) Inequality v. emissions

(b) % of simulations that meet policy objectives

Figure 3: Simulation results. The left-hand panel shows the relation between greenhouse gas emissions and inequality in the final simulation year 2050. Each point represents a different simulation. The vertical and horizontal dashed thresholds are the median values calculated from all simulations. The right-hand panel shows the percentages of simulations that meet median-based (columns 1-3) and quartile-based (columns 4-6) policy objectives.

Figure 3a shows a negative correlation between inequality and emissions, suggesting that decarbonisation efforts can have an adverse effect on income distribution. Furthermore, efforts to counterbalance this effect through economic growth may jeopardise low-carbon goals, given that GDP is positively correlated with emissions (see Figure A.1).

Figure 3b shows the percentages of simulations that meet one or multiple policy goals. Each grey column represents the whole set of 16,023 simulations. The green and violet rectangles are the subsets of simulations that meet the ‘low GHG’ and ‘low Gini’ objectives, respectively, while the blue rectangles denote the simulations that meet the ‘low GHG, low Gini’ objective and the red rectangles are the simulations that meet the ‘low GHG, low Gini, high GDP’ objective. In the first three columns, policy goals are defined based on final-period median values of emissions, inequality, and GDP; in the last three columns, objectives are instead based on top and bottom

[3] To see this note that a yearly growth rate of about 1.08 percent between 2010 and 2050 would result in a real GDP of 2.25 trillion euros at the end of the simulation. Note also that demographic change cannot explain the differences in GDP in the model, because population does not vary across simulations.

quartile thresholds. Thus, for example, the observations that meet the ‘low (below-median) GHG’ goal in the first column of Figure 3b (green rectangle) are those in quadrants 2, 3a and 3b of Figure 3a, whereas the observations that meet the ‘low Gini’ goal (violet rectangle) are those in quadrants 1, 3a and 3b. The set of observations that meet the ‘low GHG, low Gini’ goal in the second column of Figure 3b (blue rectangle) is the intersection of the green and violet rectangles in the first column; these observations are those in quadrants 3a and 3b of Figure 3a. Finally, the observations that meet the ‘low GHG, low Gini, high GDP’ goal in the third column of Figure 3b (red rectangle) are those in quadrant 3b of Figure 3a.

Approximately 20 percent of simulations ($n = 3,203$) exhibit below-median levels of Gini and emissions. When we also consider above-median GDP, this figure drops to approximately 11.5 percent of simulations ($n = 1,842$). Note that if the three indicators were uncorrelated, then 25 percent of simulations would meet the ‘low GHG, low Gini’ objective, while 12.5 percent would meet the ‘low GHG, low Gini, high GDP’ objective. Focusing on simulations with emissions and inequality levels below the bottom quartile would make achieving policy objectives even more challenging. Merely 3.1 percent of simulations ($n = 496$) meet bottom-quartile inequality-and-emissions goals, which is half of what it would be if there was no correlation. If we add the condition of above-top-quartile GDP, then only 1.1 percent of simulations ($n = 175$) remain, in contrast 1.5 percent if the three indicators were orthogonal.

Empirical studies have yielded mixed results on the existence of a trade-off between emissions and inequality, whereas the positive relation between growth and emissions has stronger support in the literature. Ravallion et al. (2000) and Rojas-Vallejos and Lastuka (2020), examining different country samples, find evidence of a trade-off. However, the former study argues that this relation is weak, while the latter suggests that it does not hold for high-income countries. Uddin et al. (2020), using a longer series of data (1870-2014) for G7 countries, provide evidence of a non-linear relation, concluding that there was a trade-off only between the 1950s and the end of the 1990s. Lastly, Jorgenson et al. (2017), examining US state data for the period 1997-2012, find no correlation between the Gini coefficient and emissions but do find a positive correlation between emissions and the income share of the top decile. These findings are consistent with our simulation results, which show that emissions and inequality reductions are not complementary but can nevertheless be achieved jointly, although at a lower frequency than if they were pursued individually.

The results also reveal that achieving a just transition becomes more challenging when pursuing GDP growth. Considering growth as a necessary condition for a low-carbon, low-inequality transition would result in discarding all parameter combinations that achieve emissions and inequality objectives at lower GDP levels. This means that all simulations falling in region 3a of Figure 3a would be excluded. These findings suggest that the policies adopted to achieve a certain objective may not be neutral with respect to other objectives, that is, pursuing one goal may negatively impact the achievement of another goal. This highlights the need to understand which policy parameters can serve either or both policy objectives, and what combinations of parameters can balance possibly contrasting forces towards a just transition.

4.2 Main policy parameters

The main results of the random forest analysis are presented in the left-hand panel of Figure 4, which shows the permutation feature importance of the 10 most important predictors for each policy objective (GHG, Gini, GHG-Gini and GHG-Gini-GDP), plotted on a logarithmic scale. The right-hand panel gives information about the direction and magnitude of the effect of each parameter, and shows the difference between the parameter's mean value calculated from the simulations that meet a certain policy goal ('low GHG', 'low Gini', 'low GHG, low Gini' and 'low GHG, low Gini, high GDP') and its mean value calculated from all 16,023 simulations.

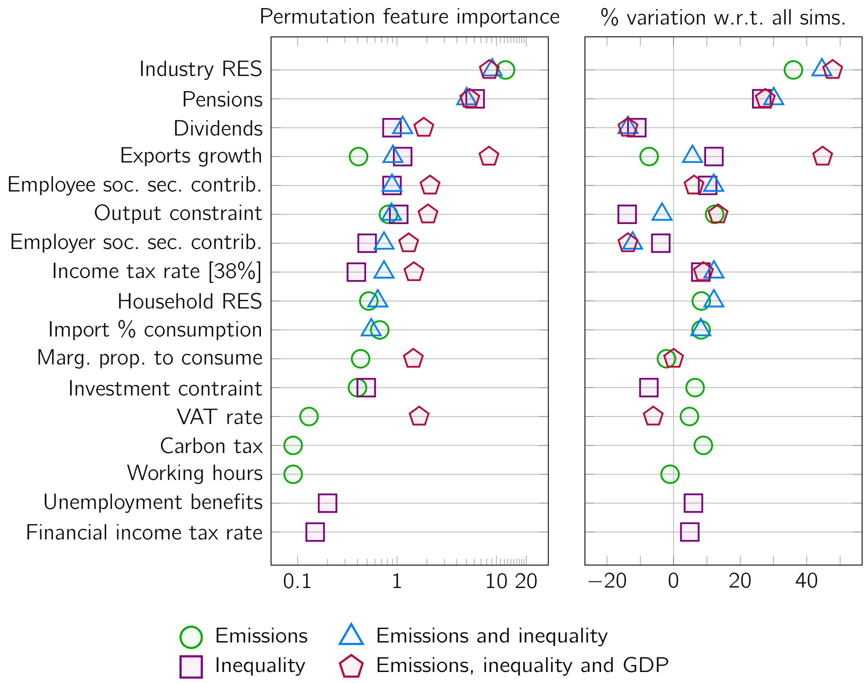


Figure 4: Main policy parameters. The two panels provide information on the 10 main parameters associated with each policy goal or combination of goals: emissions (green circles); inequality (violet squares); emissions and inequality (blue triangles); emissions, inequality and GDP (red pentagons). The left-hand panel shows the permutation feature importance of each parameter, plotted on a log scale. Higher values indicate an important predictor of the simulation outcome. The right-hand panel shows the difference between the mean value of each policy parameter calculated from all the simulations that meet a policy objective and the mean value calculated from all simulations.

The majority of key predictors can be directly related to policies. Moreover, importantly, our analysis shows that most of the parameters that strongly predict GHG emissions (indicated by green circles) do not play a major role in predicting income inequality (indicated by violet squares), and vice versa. This finding supports the view that no single intervention can be a game changer for achieving multidimensional objectives, and that a combination of measures is needed. This is further evidenced by the results obtained for the GHG-Gini and GHG-Gini-GDP cases (denoted by blue triangles and red pentagons, respectively).

In three out of four cases, the policy parameter with the highest permutation importance is the increase in the share of renewable energy sources in industry energy consumption. The right-hand panel of Figure 4 shows that if we aim for inequality reduction and GDP growth along with decarbonisation, then achieving low emission levels becomes more challenging and requires greater deployment of renewables. The increase in the share of renewable energy sources in household energy consumption also plays a role, albeit less significant, mainly due to lower household energy use and emissions compared to industry.

A critical leverage point towards a just transition is to support the lowest segments of the income distribution. In the model, pensions play a key role in this respect.[4] Although higher pensions tend to increase aggregate demand and therefore emissions, their positive effect on income distribution is much more significant, because a large proportion of pensioners are low-skilled and concentrated in the lower end of the income distribution. This also applies to unemployment benefits, which however are less effective in reducing inequality as they are directed towards a smaller subset of the population.

Another group of parameters points to the potential of addressing the income distribution from the opposite angle, that is by limiting top incomes. Here it is worth noting that, despite mounting evidence of tax dodging by the very wealthy (Saez and Zucman 2019) and of their disproportionate environmental impact (Oswald et al. 2021; IPCC 2022), policies directed at high-income earners are somewhat neglected in the EM and climate mitigation literatures. To our knowledge, there is currently no scenario-based study that explores the consequences of redistributing income away from the rich. Our analysis identifies at least three relevant parameters directly related to limiting top incomes, including lower dividends, a higher labor income tax rate in top brackets, and a higher tax rate on financial income, which can yield a double dividend by reducing inequality and limiting consumption and emissions among high earners.[5]

[4]The parameter that we let vary is the pensions-to-wage ratio, which determines gross pensions as a percentage of workers' mean annual wage.

[5]In the model, due to the aggregation of individuals into groups, the majority of high income earners consists of high-skill employed males and females falling into the third income tax bracket (28,000 to 55,000 euros per year). A notable exception is that of capitalists, who make up one percent of the total population and are assumed to earn solely

Similarly, higher employee social security contributions reduce inequality because they reduce the net labor income of employed individuals, who tend to earn more than their unemployed, retired, and out-of-the-labor-force counterparts of the same gender and skill level.

A third set of parameters suggests a negative relation between investment and inequality. Reductions in employer social security contributions, value-added tax rates, and the percentage of profits paid out as dividends tend to increase retained profits, enabling industries to finance more investment. The resulting acceleration of fixed capital formation has two main effects: on income distribution through reduced dividends, and on employment and aggregate demand through increased investment.

The potential of addressing inequality by increasing aggregate demand is confirmed by the inclusion of the output and investment constraints in the sets of strongest predictors. While these parameters are not policy measures themselves, their significance sheds light on how limiting output and investment could impact emissions and inequality. The findings in Figure 4 suggest that excluding these constraints from a simulation model tends to lead to lower inequality, while their inclusion restricts production and investment spending, resulting in lower emissions. Along a related line, a decrease in individuals' marginal propensity to consume reduces demand and thus emissions.

Exports play a uniquely relevant role as the only variable identified as a strong predictor in all four cases.[6] Since exports provide a strong stimulus to economic growth, they tend to have below-average values in simulations that meet the 'low GHG' objective, but above-average values in simulations that meet the 'low Gini', 'low GHG, low Gini', and 'low GHG, low Gini, high GDP' objectives. However, we note that relying on net exports to drive the growth and distribution of national income is not a feasible option at the global level. The same holds for the percentage of consumer goods that are imported (which is one of the strongest predictors in the GHG and GHG-Gini cases), since in the model an increase in imports roughly corresponds to exporting emissions.

Finally, the main policy parameters include working time reduction and carbon taxation, which are both central to the current debate on achieving a just transition and are well represented in our literature review. Empirical findings suggest that, on average, a small decrease in working hours results in lower emissions (Antal et al. 2020), which is consistent with our results. However, we find no evidence of the double dividend (i.e. the joint improvement of socioeconomic and environmental indicators) that is sometimes associated with working time

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from financial income.

[6]The Exports growth parameter determines the magnitude of an exogenous trend in exports. In the model, exports are also influenced by a price elasticity parameter, which however does not rank among the main predictors.

reduction (Fitzgerald et al. 2018).

The carbon tax is unsurprisingly identified as an effective means to reduce emissions, but its role is somewhat less significant than is generally credited in the environmental economics literature (Metcalf 2019; Hájek et al. 2019). Although recent evidence suggests a small effect of carbon taxation on low-carbon innovation (van den Bergh and Savin 2021), in our case the less-than-stellar impact of the tax is likely related to the aggregation level of the model. Production and energy demand are in fact modelled at the industry level, while the burden of a carbon tax can actually vary considerably within industries, with heavy polluters facing higher costs[7]. Moreover, the reason why the carbon tax does not appear among the 10 main policy parameters in the GHG-Gini case is likely due to the fact that no automatic recycling mechanism of carbon tax revenues is implemented in the model. Nonetheless, our analysis does accommodate the fact that the distributional effects of carbon taxation crucially depend on whether the tax is accompanied by compensatory measures (Callan et al. 2009; Fremstad and Paul 2019). In the model, explicit revenue recycling schemes are proxied by an increase in public benefits which is concomitant with the introduction of the carbon tax.

An interesting finding from our analysis is the absence of technological progress among the strongest predictors, which may come as a surprise given its prevalence in the literature reviewed in Section 2. This does not mean that the transition towards renewables is not influenced by new technologies. Rather, it suggests that innovations modelled at the macro level — related to labour productivity, intermediate input requirements, and energy efficiency — do not appear to play a major role. The limited impact of energy efficiency is likely related to economy-wide rebound effects (Brockway et al. 2021), which make efficiency gains lead to increased consumption (through lower prices of energy-intensive goods) and investment (through a decline in production costs and an increase in profit rates).

These findings emphasize that a low-carbon, low-inequality transition calls for a variety of measures spanning several different policy domains, certainly more than is commonly seen in the literature. They also indicate that targeted measures to address income inequality play an essential role, whereas interventions aimed at raising national income (e.g. through government expenditure or a proportional increase in wages) seem not to be as relevant. Finally, they show that policies which boost aggregate demand, mostly directed at low-income groups, are crucial to achieve a just transition, and that the adverse effects of these policies on emissions must be compensated for by measures that decarbonise the additional demand and reduce the environmental impact of the wealthy.

[7]For instance, in the electricity sector, although the industry as a whole may exhibit a relatively low emission intensity, high polluters like coal plants would typically face high carbon costs.

4.3 Low emissions, low inequality pathways

Some of the results discussed earlier can also be seen by considering the drivers of emissions and inequality summarised in Figure 5. Panel 5a shows the dynamic of greenhouse gas emissions (GHG), which are broken down into GDP, the energy intensity of production (NRG/GDP), and the emissions intensity of energy demand (GHG/NRG); panel 5b decomposes the Gini coefficient of net income (N) into the Gini coefficient of gross income before taxes and transfers (G) and the ratio between the former and the latter:

$$GHG = GDP \times \frac{NRG}{GDP} \times \frac{GHG}{NRG}, \qquad N = G \times \frac{N}{G}.$$

The figure is based on a new set of 500 simulations, performed by letting the mean and standard deviation of the distributions from which parameters are drawn be those of the simulations that jointly reached below-median emissions and inequality levels in Figure 3a. Moreover, in order to highlight the most relevant drivers of environmental and distributional outcomes, we selected the subset of simulations ($n = 55$) that reach bottom quartile emissions ($GHG \leq 146$ Mtons CO_2 eq./year.) and inequality (Gini ≤ 0.197) in the final simulation year[8].

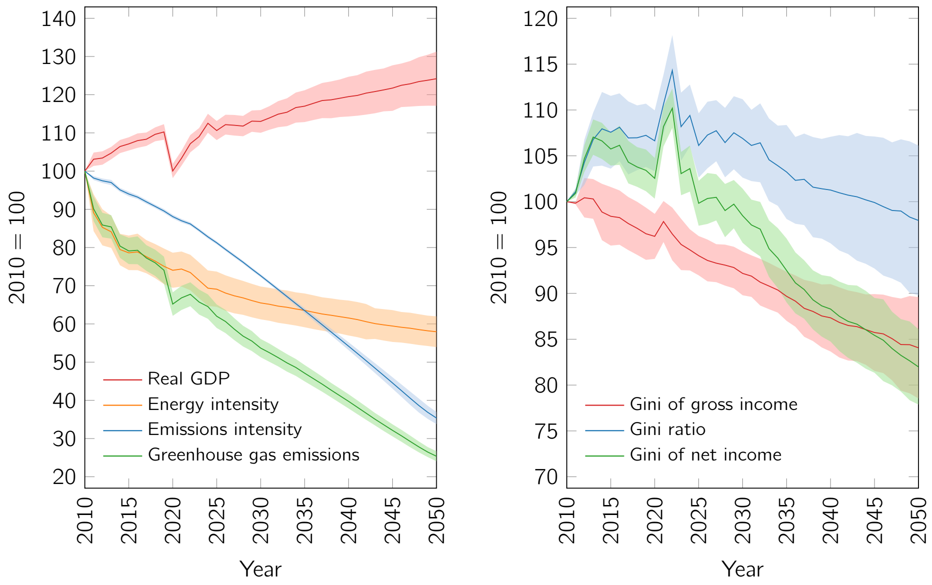
The dynamics further underline the importance of a fast expansion of renewables in all industries, as suggested in Figure 4. Improvements in energy efficiency due to technological progress slow down in 2025 and are less than enough to offset the (modest) growth of GDP. Thus, a substantial curbing of greenhouse gas emissions depends heavily on the expansion of renewable energy sources.

Panel 5b illustrates how variations in the Gini coefficient, calculated using disposable income, are affected by the evolution of market income (from labour and capital) and by the capacity of public taxes and transfers (including pensions and unemployment benefits) to redistribute income. The figure confirms the role of overall economic activity in driving inequality through changes in employment, wages and profits. However, it also underlines the importance of a more progressive tax and transfer system. The redistribution of income induced by some of the parameters listed in Figure 4 (such as dividends, labour and financial income taxes, pensions and unemployment benefits) seems to be crucial in influencing the Gini coefficient of net income, and contributes to its sharper decline after 2030.

5 Concluding remarks

The simulation exercise presented in this study focuses on the simultaneous reduction of emissions and inequality, and identifies combinations of model parameters that promote a just low-

[8]These are the bottom quartile values calculated from all simulations shown in Figure 3a.



(a) Simplified Kaya identity

(b) Gini coefficient decomposition

Figure 5: Decomposition of emissions and inequality. The left-hand panel decomposes greenhouse gas emissions into real GDP, net inland energy consumption divided by GDP (energy intensity), and total emissions divided by net inland energy consumption (emissions intensity). The right-hand panel decomposes the Gini coefficient of net income into the Gini coefficient of gross income and the net-to-gross Gini ratio. Both panels plot the means and one standard deviation confidence intervals.

carbon transition. The results discussed in Section 4.1 also indicate that the pursuit of continuous economic growth narrows the path to achieving low-emissions-and-inequality goals.

The expansion of renewable energy sources is found to be an essential pre-condition for decarbonisation, and can be complemented by carbon taxes, measures that discourage consumption, and working time reduction. Policies that affect the distribution of income are also crucial and should be designed to work in synergy with one another: the increase in demand and emissions caused by transfers and benefits targeted at low-income groups can in fact be partially offset by policies that limit top incomes, which reduce the emissions of high earners while at the same time improving the income distribution. Increases in aggregate demand components, such as investment and exports, tend to impact positively on growth and income equality but also result in a direct increase in emissions. Finally, a notable absence among the main policy parameters are those directly related to energy efficiency. We interpret these results as suggesting that a just transition will require a progressive tax and benefits system that redistributes income without major increases in aggregate demand, coupled with a considerable increase in renewable generation capacity.

Our simulations encompass the case of a carbon tax accompanied by progressive tax reductions and transfers, the only difference being that in our model there is no earmarking of tax revenues. However, the opposite is not true, that is, the policies discussed in this paper cannot be subsumed into a carbon tax with progressive revenue recycling. Furthermore, although there is convincing evidence that revenue recycling can more than offset the regressive impact of carbon taxation (Williams et al. 2015; Budolfson et al. 2021), it is uncertain whether it can serve as a one-size-fits-all solution that allows for a sufficient reduction in inequality alongside a decrease in emissions.

The sets of policy parameters identified by random forests as the most important to reduce emissions and inequality have only a few elements in common. Thus, in contrast to the majority of studies reviewed in Section 2, the joint pursuit of these two goals is likely to require a number of simultaneous measures. A related point is that studies which examine policies in isolation or in very small groups risk under- or overestimating the necessary scale of these measures. For instance, the yearly growth rate of renewable energy used in the baseline of our model replicates the rates predicted by Italy's Integrated National Energy and Climate Plan (MISE-MATTM-MIT 2019), according to which renewables will supply 55% of electricity demand, 22% of transport energy demand and 30% of total energy demand by 2030 (starting from 34.1, 5.5 and 18.3% in 2020, respectively). However, the mean growth rate of renewable energy sources in industry calculated from the simulations that meet the 'low GHG, low Gini ' objective is some 40% higher than the baseline, mainly due to the need to offset the increase in energy demand caused by redistributive policies directed at low income groups. By 2030 this would result in a share of renewables of about 64% in electricity consumption, 36% in transportation and 35% in total energy consumption. Thus, commitment by governments to jointly achieve distributional and low-carbon goals will make it necessary for them to increase renewables at a significantly faster pace than if climate mitigation were pursued without regard to, or even at the expense of, equity issues.

Data and code availability

The complete results of the literature review, the Vensim code for the model, the database of simulations, and the Stata and R scripts to replicate the results are available for download at Zenodo (DOI: 10.5281/zenodo.5711126). All files are open access and subject to a Creative Commons Attribution 4.0 International Public License (CC BY 4.0).

Authorship statement

NC: methodology (model development, programming), investigation (model input data), data curation, formal analysis, visualisation, writing (original draft). *MC:* methodology (model development). *AC:* conceptualisation, supervision, methodology (model development, programming, calibration, simulations), investigation (model input data, literature review), data curation, formal analysis, visualisation, writing (original draft). *SD:* methodology (model development), project administration, funding acquisition. *TD:* methodology (model development, programming), investigation (model input data), data curation, writing (original draft). *PG:* investigation (literature review). *TH:* methodology (model development, programming, simulations), investigation (model input data), data curation, formal analysis, writing (original draft).

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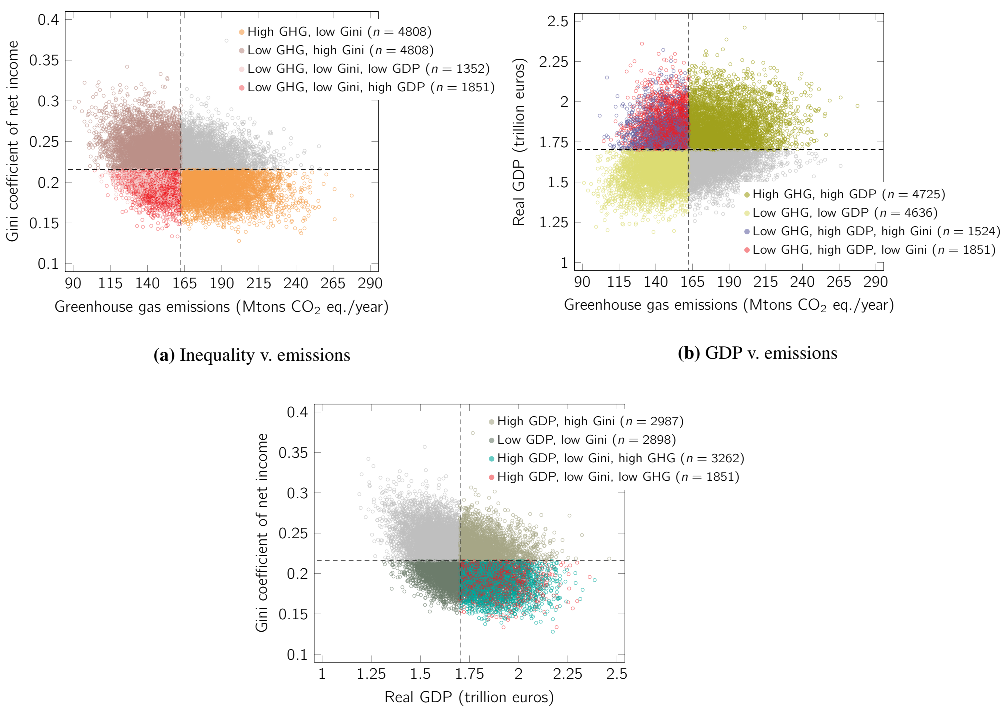
Appendix

This appendix presents additional results and details on data processing and analysis. Section A complements Section 4 in presenting our findings. Section B provides a series of robustness checks, showing that the random forest results hold under a variety of resampling methods to deal with imbalanced data. The parameter value ranges used to generate the simulation dataset are listed in Section C.

A Additional results

A.1 Emissions, inequality and GDP

Figure A.1 shows the relation between greenhouse gas emissions, inequality, and GDP in the final simulation year. Each point represents a different simulation. The vertical and horizontal dashed lines represent the median values calculated from all simulations.



(a) Inequality v. emissions

(b) GDP v. emissions

(c) Inequality v. GDP

Figure A.1: Inequality, emissions and GDP in the final simulation year

A.2 Partial dependence plots

Figures A.2, A.3, A.4 and A.5 show the impact of policy parameters on Prob (low GHG), Prob (low Gini), Prob (low GHG, low Gini) and Prob (low GHG, low Gini, high GDP), respectively. The black curves (one for each observation in the training sample) are the individual conditional expectations describing how the probability of the desired policy outcome changes with the value of a certain parameter of interest, keeping all other parameters constant at their respective last-period level (Goldstein et al. 2015). The green, purple, blue and red curves are the partial dependence plots obtained by averaging over all observations. Each plot is anchored at the lower end of the value range, and shows the difference in the prediction with respect to that point. The blue ticks at the bottom of each panel represent the deciles of the parameter distribution.

A.2.1 Policy objective: emissions

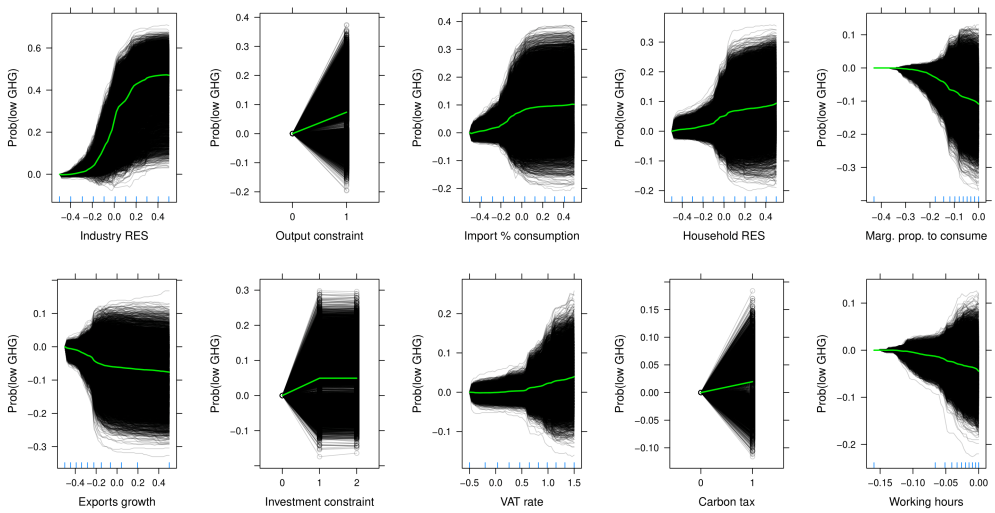


Figure A.2: ICEs and PDPs of the 10 main policy parameters (objective: GHG)

A.2.2 Policy objective: inequality

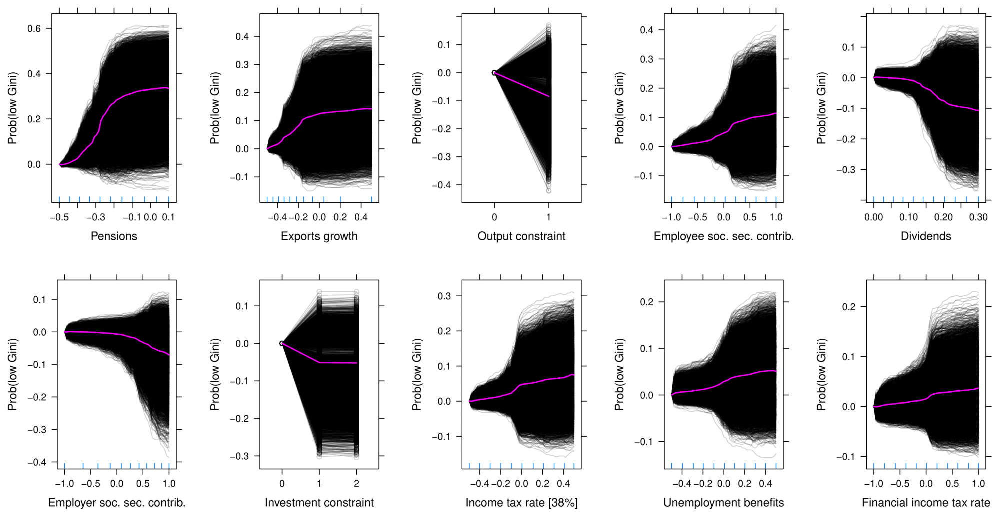


Figure A.3: ICEs and PDPs of the 10 main policy parameters (objective: Gini)

A.2.3 Policy objectives: emissions and inequality

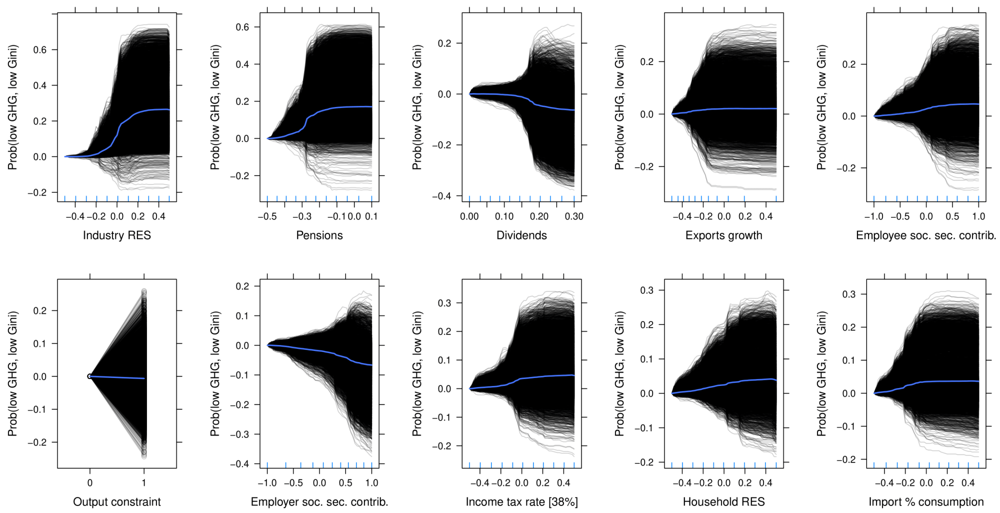


Figure A.4: ICEs and PDPs of the 10 main policy parameters (objective: GHG-Gini)

A.2.4 Policy objectives: emissions, inequality and GDP

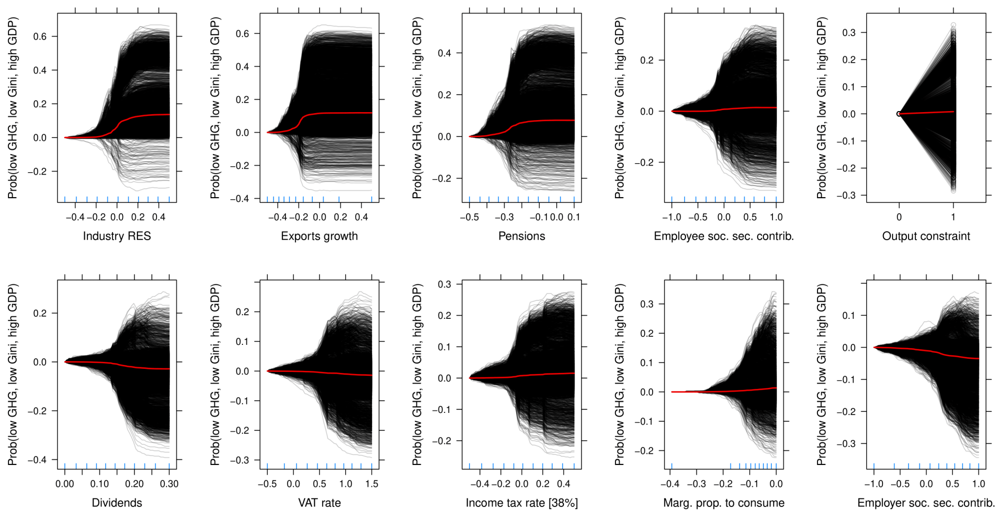


Figure A.5: ICEs and PDPs of the 10 main policy parameters (objective: GHG-Gini-GDP)

A.3 Kernel densities

Figure A.6 shows the kernel density distribution of the main continuous policy parameters. The coloured lines describe the distribution of input parameters in the subset of simulations that meet a certain policy goal: low emissions (green); low inequality (purple); low emissions and low inequality (blue); low emissions, low inequality and high GDP (red). The black dashed lines represent the parameters' distribution across all simulations. In all panels the number of observations decreases near the extremes of the range of possible values; this is because the simulations dropped from the dataset (due to economically meaningless or unreasonable results) are typically those featuring extreme values of policy parameters.

B Robustness checks

As discussed in Section 4, when simultaneously considering emissions and inequality, the four classification categories — 'high GHG, high Gini', 'high GHG, low Gini', 'low GHG, high Gini' and 'low GHG, low Gini' — are not equally represented in the data. In particular, the observations in the 'low GHG, low Gini' region of Figure 3a are relatively fewer in number than those in the 'low GHG, high Gini' and 'high GHG, low Gini' regions. A consequence of this mild class imbalance is that the random forest model will tend to overlook, and therefore have

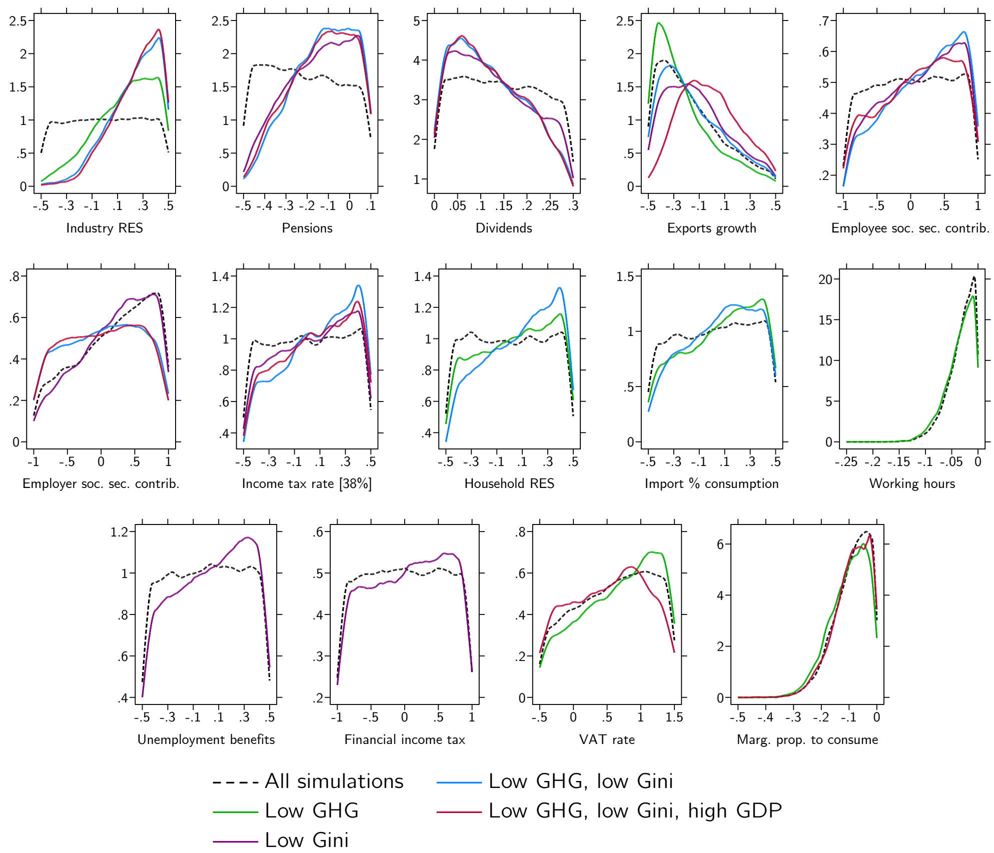


Figure A.6: Kernel density distribution of the 10 main continuous policy parameters

poor prediction performance on, the ‘low GHG, low Gini’ class, which however is the class we are most interested in.

A common method to deal with class imbalances is to resample the dataset, either by undersampling the majority classes or by oversampling the minority classes. The undersampling approach involves drawing observations at random from the majority classes and dropping them from the training dataset, so as to balance the class distribution before training the model; conversely, the oversampling approach consists in randomly duplicating observations from the minority classes and adding them to the training dataset. Yet another method is to synthesize new observations from the minority classes using the Synthetic Minority Oversampling Technique (SMOTE). This method consists in randomly drawing a minority class observation, finding its m nearest neighbours in terms of characteristics, and choosing one of these neighbours at random; the synthetic observation is created as a convex combination of the two neighbours, that is at a random point on the line connecting them.

Following common practice in the literature, we combined undersampling and synthetic minority oversampling methods (Chawla et al. 2002), with the number nearest neighbours m

equal to 5. For example, in the GHG-Gini case, we downsampled the majority classes — 'high GHG, low Gini' and 'low GHG, high Gini' — by a factor of about 0.83 and then synthetically oversampled the minority classes — 'high GHG, high Gini' and 'low GHG, low Gini' — by a factor of 1.25. This reduced the number of observations in the training dataset from 11,214 to 11,198, i.e. about 2,800 observations per class. Table B.1 gives the numbers of observations in the original training dataset, in the SMOTEd-and-undersampled dataset, and in the datasets resulting from 3 alternative resampling methods: undersampling, oversampling, and SMOTE without undersampling.

Table B.1: Training sample sizes under different resampling methods

	No resampling	Majority undersampling	Minority oversampling	SMOTE	SMOTE & majority undersampling
Objective: GHG					
n high GHG	5,608	-	-	-	-
n low GHG	5,608	-	-	-	-
n (overall)	11,216	-	-	-	-
Objective: Gini					
n high Gini	5,608	-	-	-	-
n low Gini	5,608	-	-	-	-
n (overall)	11,216	-	-	-	-
Objectives: GHG and Gini					
n high GHG, high Gini	2,242	2,242	3,365	3,365	2,800
n high GHG, low Gini	3,365	2,242	3,365	3,365	2,799
n low GHG, high Gini	3,365	2,242	3,365	3,365	2,799
n low GHG, low Gini	2,242	2,242	3,365	3,365	2,800
n (overall)	11,214	8,968	13,460	13,460	11,198
Objectives: GHG, Gini and GDP					
n high GHG, high Gini, high GDP	1,006	952	2,323	2,322	1,700
n high GHG, high Gini, low GDP	1,215	952	2,323	2,323	1,699
n high GHG, low Gini, high GDP	1,069	952	2,323	2,322	1,700
n low GHG, high Gini, high GDP	2,304	952	2,323	2,322	1,699
n high GHG, low Gini, low GDP	2,323	952	2,323	2,322	1,700
n low GHG, high Gini, low GDP	1,066	952	2,323	2,323	1,700
n low GHG, low Gini, high GDP	1,279	952	2,323	2,322	1,699
n low GHG, low Gini, low GDP	952	952	2,323	2,322	1,700
n (overall)	11,214	7,616	18,584	18,578	13,597

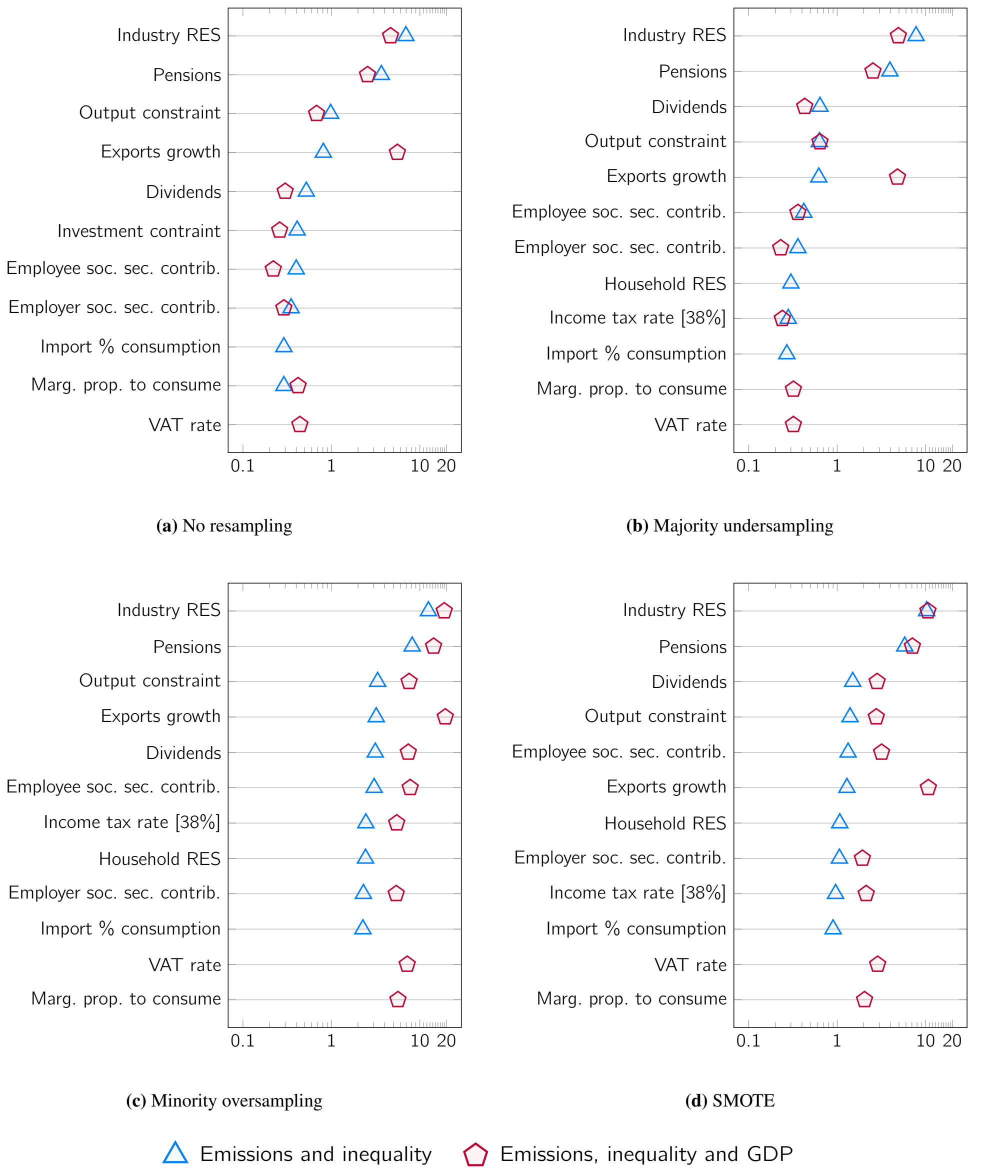
Table B.2 compares the prediction accuracy, sensitivity (true positive rate) and specificity (true negative rate) of random forest models trained on the original and resampled datasets. All random forests were based on 500 classification trees built on bootstrapped training samples.

At each split in each tree, a random sample of 10 out of 107 parameters was chosen as split candidates. The results of the GHG-Gini case indicate that all resampling methods improve the sensitivity of the ‘low GHG, low Gini’ class at the cost of some decrease in specificity and overall accuracy. No technique clearly dominates the others; the SMOTE-and-undersamping method was chosen as the preferred option because it represents a reasonable compromise between sensitivity and accuracy. For consistency, this resampling method was also used in the GHG-Gini-GDP case, although in this case the the oversampling approach approach yields slightly better results in terms of both accuracy and sensitivity of the ‘low GHG, low Gini, high GDP’ class.

Figure B.1 shows that the random forest results are robust to whether and how training data are resampled. The four panels report the permutation feature importance of the main policy parameters in the imbalanced case and for each resampling method (the results obtained in the SMOTE-and-undersampling case are shown in the left-hand panel of Figure 4). The set of 10 policy parameters with the greatest predictive power remains essentially unchanged (with some minor exceptions in the imbalanced case with no resampling), and their ranking is similar for all resampling methods. This indicates that our arguments do not hinge on specific data processing choices.

Table B.2: Prediction accuracy of the random forest models under different resampling methods

	No resampling	Majority undersampling	Minority oversampling	SMOTE	SMOTE & majority undersampling
Objective: GHG					
Overall accuracy	.830	-	-	-	-
Sensitivity	.826	-	-	-	-
Specificity	.834	-	-	-	-
Objective: Gini					
Overall accuracy	.811	-	-	-	-
Sensitivity	.794	-	-	-	-
Specificity	.826	-	-	-	-
Objectives: GHG and Gini					
Overall accuracy	.672	.647	.671	.658	.652
Sens. high GHG, high Gini	.518	.704	.583	.634	.664
Sens. high GHG, low Gini	.769	.618	.711	.667	.639
Sens. low GHG, high Gini	.833	.559	.704	.642	.599
Sens. low GHG, low Gini	.556	.765	.650	.692	.739
Spec. high GHG, high Gini	.946	.880	.926	.904	.894
Spec. high GHG, low Gini	.821	.885	.847	.866	.876
Spec. low GHG, high Gini	.756	.913	.854	.875	.893
Spec. low GHG, low Gini	.948	.856	.924	.895	.873
Objectives: GHG, Gini and GDP					
Overall accuracy	.552	.520	.563	.545	.532
Sens. high GHG, high Gini, high GDP	.267	.512	.363	.484	.449
Sens. high GHG, high Gini, low GDP	.485	.601	.589	.620	.595
Sens. high GHG, low Gini, high GDP	.807	.442	.673	.484	.541
Sens. low GHG, high Gini, high GDP	.358	.519	.413	.501	.505
Sens. high GHG, low Gini, low GDP	.385	.558	.456	.529	.506
Sens. low GHG, high Gini, low GDP	.800	.446	.700	.513	.570
Sens. low GHG, low Gini, high GDP	.526	.568	.586	.552	.563
Sens. low GHG, low Gini, low GDP	.223	.670	.430	.643	.608
Spec. high GHG, high Gini, high GDP	.989	.938	.978	.946	.956
Spec. high GHG, high Gini, low GDP	.956	.929	.944	.932	.934
Spec. high GHG, low Gini, high GDP	.829	.940	.877	.931	.917
Spec. low GHG, high Gini, high GDP	.973	.932	.959	.935	.944
Spec. high GHG, low Gini, low GDP	.970	.918	.950	.930	.929
Spec. low GHG, high Gini, low GDP	.803	.959	.872	.937	.928
Spec. low GHG, low Gini, high GDP	.956	.933	.941	.927	.931
Spec. low GHG, low Gini, low GDP	.986	.907	.965	.927	.938



(a) No resampling

(b) Majority undersampling

(c) Minority oversampling

(d) SMOTE

Figure B.1: Permutation feature importance of the 10 main policy parameters under different resampling methods

C Simulation parameters

Table C.1 lists all parameters that vary across simulations. Based on their characteristics, they were grouped into Structural parameters, Non-calibration parameters, and Calibration parameters. References to the equations in the model documentation are given in the last column of the table.

Non-calibration parameters follows a linear trend, starting from a fixed value in 2022 and reaching a randomly selected value in the final simulation year. Conversely, Structural and Calibration parameters are randomly drawn in the first period and then remain fixed throughout the simulation run. The value range of Non-calibration parameters generally spans from -50 to $+50$ percent of their initial level, except when a different value range was available from cross-country comparisons. The *Working hours*, *Marginal propensity to consume*, and *Carbon tax rate* parameters were drawn from a half-normal (rather than uniform) distribution in order to focus on moderate, more plausible and politically feasible parameter values. Finally, as discussed in Section 3.2, Calibration parameters span a smaller range of values because they are calibrated to fit historical data.

The letter i within parentheses indicates that an independent random draw is made for each of the 19 industries featured in the model. Thus, for example, the sensitivity of investment to capacity utilisation is determined at the industry level by 19 independent draws. Similarly, the letters c and s indicate that a draw is made for each of the 16 consumption categories and 3 skill levels, respectively. The total number of random draws per period is 107.

Table C.1: List of sensitivity parameters

Parameter	Unit	Min	Max	Distribution	Baseline	Equation
Structural parameters						
Investment constraint	{0,1,2}	0	2	vector	2	2.27,2.27'
Output constraint	{0,1}	0	1	vector	1	2.4'
Carbon tax	{0,1}	0	1	vector	0	2.20
Warming scenarios	{1,2,3,4}	0	4	vector	1	2.159
Non-calibration parameters						
Skill supply trends	%	-0.5	+0.5	continuous uniform	0	2.63
Depreciation rates	%	-0.5	+0.5	continuous uniform	0	2.30
Equity-to-liabilities ratio	%	-0.5	+0.5	continuous uniform	0	2.27
Import share of consumption	%	-0.5	+0.5	continuous uniform	0	2.7
Import share of government final demand	%	-0.5	+0.5	continuous uniform	0	2.9
Import share of investment spending	%	-0.5	+0.5	continuous uniform	0	2.8
Exports growth rate	%	-0.5	+0.5	continuous uniform	0	2.11
Households' RES growth rate	%	-0.5	+0.5	continuous uniform	0	2.145,2.148
Industries' RES growth rate	%	-0.5	+0.5	continuous uniform	0	2.145,2.147
Change in technical coefficients	%	-0.5	+0.5	continuous uniform	0	
Change in labour productivity	%	-0.5	+0.5	continuous uniform	0	
Tax rate on financial income[9]	%	-1	+1	continuous uniform	0	2.85
Employee social security contrib.[10]	%	-1	+1	continuous uniform	0	2.77
Employer social security contrib.[11]	%	-1	+1	continuous uniform	0	2.78

[9] https://tinyurl.com/3k6nfjkd
[10] https://tinyurl.com/v9szn9kv
[11] https://tinyurl.com/334mc44v

VAT rate[12]	%	-0.5	+1.5	continuous uniform	0	2.87
Corporate income tax rate[13]	%	-0.6	+0.6	continuous uniform	0	2.89
Government expenditure trend	%	-0.5	+0.5	continuous uniform	0	2.102
Unemployment benefits to wage ratio[14]	%	-0.5	+0.5	continuous uniform	0	2.93
Pension to wage ratio[15]	%	-0.5	+0.1	continuous uniform	0	2.96
Sickness and disability benefits	%	-0.5	+0.5	continuous uniform	0	2.117 – 2.120
Family and children benefits	%	-0.5	+0.5	continuous uniform	0	2.98
Other benefits	%	-0.5	+0.5	continuous uniform	0	2.120
Income tax rate [0.23]	%	-0.5	+0.5	continuous uniform	0	2.83
Income tax rate [0.27]	%	-0.5	+0.5	continuous uniform	0	2.83
Income tax rate [0.38]	%	-0.5	+0.5	continuous uniform	0	2.83
Income tax rate [0.41]	%	-0.5	+0.5	continuous uniform	0	2.83
Income tax rate [0.43]	%	-0.5	+0.5	continuous uniform	0	2.83
Working hours	%	-0.25	0	$N(0, 0.05)$	0	2.69
Marginal prop. to consume	%	-0.5	0	$N(0, 0.1)$	0	2.122
Carbon tax rate	%	0	10	$N(3, 2.5)$	0	2.20
Calibration parameters						
Technologies probability sens.		9	15	continuous uniform	11.93	2.13-14
Initial prob. labour-saving innov.	%	0.35	0.75	continuous uniform	0.67	2.13
Initial prob. intermediate-input-saving innov.	%	0.35	0.75	continuous uniform	0.47	2.14
Skill transition sens. (s)		0.65	0.85	continuous uniform	[0.69,0.75]	2.63-65
Labour force participation sens. (s)	%	0.65	0.85	continuous uniform	0.75	2.68
Gender employment subst. sens. (s)		0	0.1	continuous uniform	[0.03,0.08]	2.72

[12] https://tinyurl.com/5k9j9cac
[13] https://tinyurl.com/ufvztxph
[14] https://tinyurl.com/ymyu3xu7
[15] https://tinyurl.com/mez7354w

Wage sens. to employment		0.35	0.55	continuous uniform	0.45	2.73
Wage sens. to lab. productivity		0.7	1	continuous uniform	0.99	2.73
Wage sens. to price		0.7	1	continuous uniform	1	2.73
Investment sens. (i)		0	0.35	continuous uniform	[0,0.225]	2.22
Dividends rate	%	0	0.3	continuous uniform	0.3	2.40
Interest on loans sens.		0	0.25	continuous uniform	0.12	2.36
Price-elasticity of exports	%	0	-1	continuous uniform	-0.5	2.11
Price-elasticity of consumption (c)	%	0	-1.5	continuous uniform	0	2.131
Mark-up sens. (i)		0	0.05	continuous uniform	[0,0.067]	2.112
Seed		0	5,076	discrete uniform	1	

Structural parameters can take the integer values listed in column 2. Policy parameters vary in percentage according to the outcome of a random draw from a uniform or half-normal distribution. Calibration parameters are drawn from a uniform distribution. The extremes of the support of the distributions are given in columns 3 and 4. The footnotes contain references to the sources used to define plausible value ranges.