Exploring policy interventions for a just low-carbon transition: a scenario discovery approach

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Abstract

The concept of a just low-carbon transition is gaining academic and political traction. However, the question how can a just transition be achieved and which policy tools are important remains to be addressed in a comprehensive way in the ecological macroeonomics literature. We aim to close this gap by scrutinizing the path towards a just transition and the role a wide range of potential policies play therein. We do so by applying an extended scenario discovery approach to a revised version of the EUROGREEN model, using random forest algorithms to identify the most relevant single policies. Our results underline a trade-off between emissions and inequality, via growth, implying a somewhat narrow path towards a just transition. However, certain policy mixes are able to inhibit this trade-off allowing for a just transition featuring limited growth. Here, the expansion of renewable energy supply and policies directly addressing the income distribution are particularly prevalent. In general, there is little common ground between policies aimed at emissions and inequality, calling for a wide range of coherent policies when stirring the economy towards a just transition.

JEL Classification: Q56, Q57, C63

1 Introduction

Seldom before have concerns about the environment and inequality been so closely related. Evidence from surveys conducted around the world shows that inequality and climate change are frequently identified as 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 just transition, which calls for actions ensuring a fair and equitable transition for all individuals (McCauley and Heffron 2018; O'Neill et al. 2018). A related principle seems to have started permeating the way some policymakers conceive of 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; Hardt and O'Neill 2017). 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). Also, they share a general skepticism about the possibility of achieving an absolute decoupling of economic activity from environmental pressures (Haberl et al. 2020).

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 of inquiry 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 (Fontana and Sawyer 2016; Jackson and Victor 2016). Inevitably, this modelling stance influences the kinds of policies EM seeks to examine: as detailed in Section 2, most studies are concerned with the impact of environmental policies; the cases of policy mixes consisting of socioeconomic or socioeconomic-and-environmental measures are considerably fewer in number.

A related but different point is that the standard approach in EM is to consider preconceived scenarios featuring a small number of policies. This approach consists in choosing one or more (usually two) policies that are deemed relevant to the context being studied, translating it into suitable input parameters, and then 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 possible policy space is left unexplored.

Building on these arguments, this paper proceeds in the opposite direction, taking a scenario discovery standpoint (Lempert et al. 2006; Groves and Lempert 2007; Gerst et al. 2013) to assess how narrow the path towards a low-carbon, low-inequality transition is. We introduce a revised version of the Eurogreen model (D'Alessandro et al. 2020) and use data from about 16,000 simulation runs to identify policy bundles addressing distributive and climate issues. Our findings and recommendations are the result of an ex-post assessment. First, the model is repeatedly run within the feasible parameter space; in each simulation, more than one hundred parameters are randomly drawn from a wide range of possible values. Second, random forest algorithms are applied to the database of simulation results to understand which parameter combinations can simultaneously improve social, economic and ecological indicators. Finally, successful combinations are translated into policy prescriptions. The paper seeks to go some way towards answering important questions: Is there a trade-off between reducing emissions and inequality? To what extent is this relation mediated by economic growth? Which policy combinations make these objectives compatible? Has the literature overlooked relevant policy alternatives?

The remainder of the paper is structured 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 introduces our scenario discovery approach. Section 4 reports our main results and discusses their policy implications. Section 5 concludes and suggests avenues for further research.

2 Scenarios and policies in ecological macroeconomics

To place our work in proper perspective, we conducted a systematic review of the use of scenarios in the EM literature. The choice to restrict the analysis to this area of research was motivated by considerations of 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 in the Supplementary material.

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.

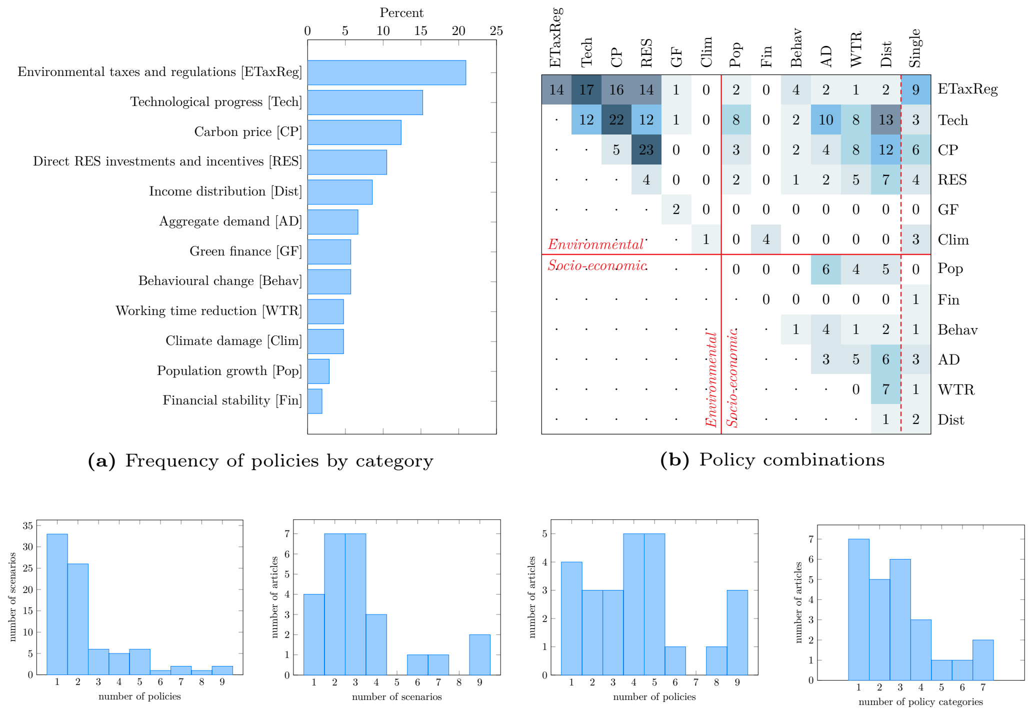
The next step was to determine how many scenarios were simulated in each article and what policies comprised each scenario. To do so, we went through all articles and identified all input parameters that varied across simulations. Often these exogenous parameter changes are framed as hypotheses rather 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 and contributions. 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 or 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.[1] 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 especially so 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 but five

[1] 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.

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 issue is further discussed in Section 5 after our main results have been presented.

3 Methods

3.1 The Model

The Eurogreen model is based on Post-Keynesian economic theory, applying system dynamics and stock-flow consistent methodological approaches to model economic, social and environmental dimensions. It is defined at the country scale and has been applied to France (D'Alessandro et al. 2020; Cieplinski et al. 2021) and Italy (Cieplinski et al. 2021). The calibration is grounded on data from the Italy between 2010 – 2019/2020. Exogenous shocks on private consumption, investments, exports and imports were added to model the impact of the Covid-19 pandemic. The simulations run from 2010 to 2050 for the Italian economy.

In what follows, we outline the model structure and dynamics necessary to interpret the results, paying particular attention to the new features included, for the first time, in this version. A detailed documentation of the model can be found in the Supplementary Material.

Aggregate demand drives production (D'Alessandro et al. 2020) and consists of exports and government consumption, which are primarily driven by exogenous trends, household consumption and gross fixed capital formation.

Households' consumption is determined by disposable income and income dependent propensities to consume. Then, consumption allocation among 16 different goods[2] is affected by price changes whose elasticities range from 0 to 1.5. Disposable income depends on government transfers (e.g. unemployment benefits or pensions), labour and financial incomes, social security contributions, income and financial income taxes. These differ according to skill, gender and employment status – employed, unemployed, out of labour force and retired – with the top 1% of individuals designated as capitalists or rentiers which earn only financial income. Here, a first novelty is the incorporation of gender differences between individuals, leading to a total of 25 different population groups. This allows for a thorough analysis of distributional aspects, now also gender specific. The dependence of consumption behaviour on income and prices supports feedback effects of distributional changes on the economy and facilitates reaction to price changes that follow, for instance, technological progress, wage increases or the introduction of a carbon tax.

Employment is also defined by skill and gender. It is determined as a function of industry-specific labour productivity, past period output, weekly hours of work. The skill composition of labour demand follows industry-specific trends while the gender composition depends on the difference between gender specific unemployment rates within each of the three skill levels. Pensions and unemployment benefits are defined in proportion to wages that, in turn, are tied to labour productivity, inflation and group specific employment rates. Financial income is derived from the interest paid by the government on bonds and dividends on equity.

Industries adjust the desired investment level on the base of the difference between the actual and a normal rate of capacity utilisation, striving to produce at the normal rate of capacity utilisation. Investments however are restricted by profits which determine the maximum investment for each industry. Another novel mechanism built into this version,

[2]The private consumption is divided on the base of the Classification of Individual Consumption According to Purpose (COICOP).

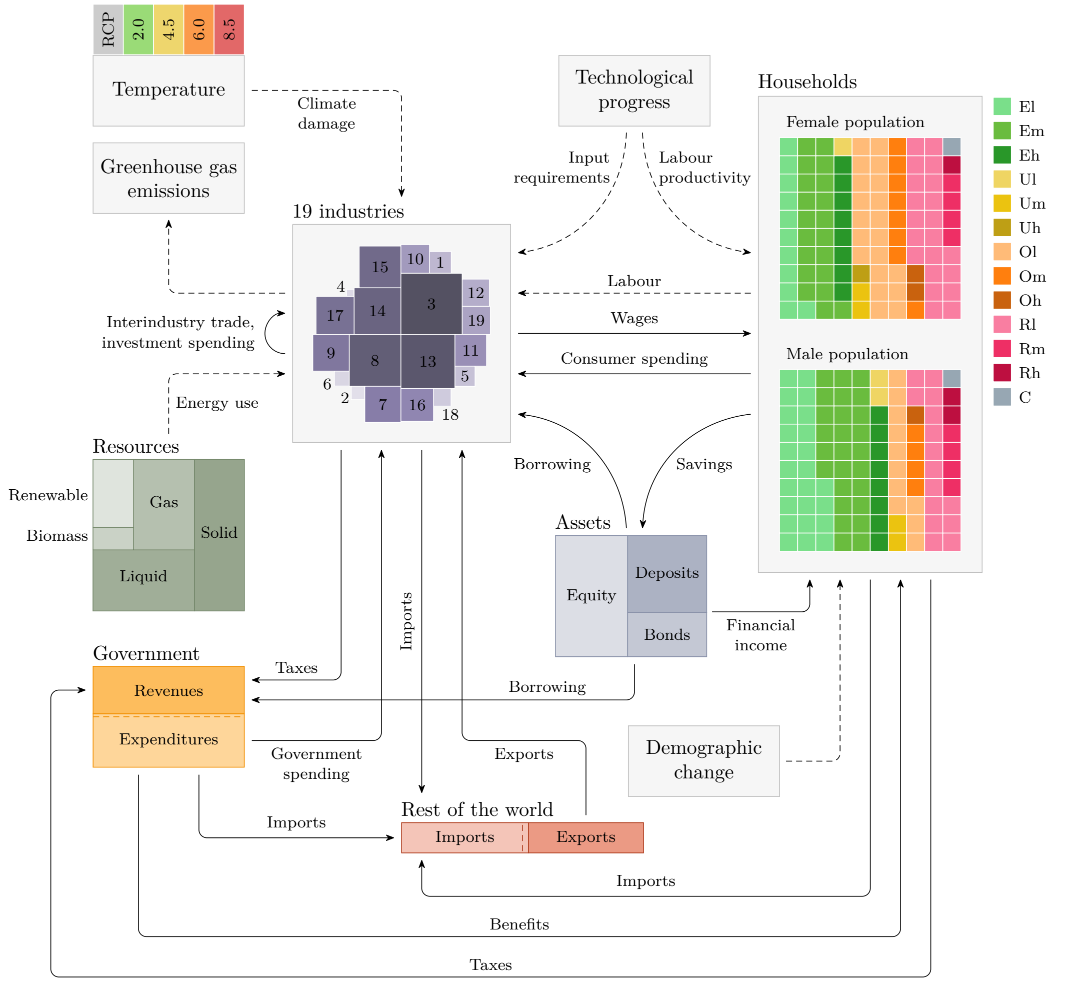


Figure 2: Model overview. The solid and dashed arrows represent monetary and non-monetary flows, respectively. The Households, Industries, Resources, Assets, Government, and Rest of the world boxes summarily represent first-period simulation results. The dashed lines in the Government and Rest of the 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.

is that in some scenarios financing conditions are also a negative function of industries' leverage.

Output is obtained multiplying domestic final demand by the Leontief inverse matrix and is also bound by the maximum product which depends on every industries' fixed capital and capital productivity. The technical coefficients of the input-output system vary with endogenous technological progress. The innovation process can be summarized as follows: in each period, at least one of four alternative technologies[3] becomes available with a certain probability, which depends on the ratio between the growth rates of unit intermediate-inputs and

[3] The four cases are: *T0.* previous period technology, *T1.* labour-saving and intermediate inputs augmenting, *T2.* intermediate inputs-saving and labour augmenting, and *T3.* intermediate input- and labour-saving.

labour costs. Hence, technologies that save on inputs becoming relatively more expensive are more likely to be extracted.[4] Once a new technology is available, the scale of variations in labour productivity and technical coefficients is also extracted from distributions calibrated to the historical trends of these variables. Subsequently, each industry chooses and implements the cost-minimising technology option. The present version of EUROGREEN now allows for efficiency improvements even in the absence of new innovations due to continuous implementation of the latest extracted technology, driven by investments and the replacement of fixed capital.

Technological progress also affects energy demand by increasing energy efficiency. Energy flows are linked to monetary flows, in real terms, of domestic production and consumption 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 then divided into 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 Ministero dell'Ambiente e della Tutela del Territorio e del Mare - Ministero dello Sviluppo Economico - Ministero delle Infrastrutture e dei Trasporti (2020). CO_2 and greenhouse gas emissions are then determined, once again, using industry and household specific energy source-to-emissions conversion coefficients. This approach guarantees that not only absolute changes in the amount of inputs required for production, but also their composition between supplying industries affects energy demand and emissions.

This version also includes, for the first time, climate damage functions that depend on exogenous representative concentration pathways (RCPs), similar to those modelled in Desmet and Rossi-Hansberg (2015). Industry specific damages are drawn from a beta distribution and deducted from final output and, thus, are equivalent to an increase in unit production costs. Population dynamics are exogenous. The Government collects social security contributions, personal income and financial taxes, corporate income and value added taxes and, when active, carbon taxes. It also provides transfers to households and engages in final consumption. Prices are determined via a markup over unit full costs of production.

Even though this version already addresses several shortcomings of the original version – such as the inclusion of damage functions, 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 – some shortcomings worth mentioning persist. The energy transition towards renewables is driven by exogenous trends, thus not receiving any feedback from the evolution of other socio-economic variables of the model, however their feasibility is guaranteed since the trends correspond to the national targets[5].

The level of aggregation of industries and groups of individuals also has consequences for the results. These are specifically relevant for income and carbon taxes. The lack of within group variability in income results in a very limited number of individuals paying income tax rates on the two highest brackets. The homogeneity of emissions within industries also reduces the carbon tax capacity to incentive renewable energy adoption among the highest polluting plants within an industry. Moreover, homogeneous groups of income earners tend to reduce inequality due to lower income dispersion on the top end of the distribution. Finally, the model does not consider how the use of natural resources might impact the local ecological processes (e.g., biodiversity loss, water pollution) nor include non-energetic resources (e.g., water, land, raw materials).

3.2 Simulation and data analysis approach

We apply the so-called *scenario discovery* approach (Lempert et al. 2006; Groves and Lempert 2007; Gerst et al. 2013) which applies "statistical or data-mining algorithms to find easy-

[4]New technologies which save both factors are always less likely to be extracted.

[5]More precisely, the share of all energy demand covered by renewables is driven by an exogenous trend, total energy demand depends directly on output and, therefore, on the level overall level of economic activity and on intermediate-inputs-saving technological progress.

to-interpret, policy-relevant regions in the space of uncertain input parameters to computer simulation models" (Bryant and Lempert 2010, p.35). Inspired by an agnostic viewpoint, we extend these applications by including also parameters that might mirror policy measures or behavioural changes. This decision allows us to avoid any arbitrary ex-ante restriction to possible pathways toward just transition and to spotlight on the role of so far neglected or ignored policy options and combinations. This leads us to elaborate a thought experiment, based on numerical simulations, by letting all selected parameters (107 in total) vary according to specific distributions within a plausible range (see Appendix for a list of varied parameters and their respective distributions). Subsequently, we compare all the simulation outcomes to assess the composition and the extension of parameter space to strive towards the respective policy goal. Hence, we extend the concept of scenario discovery to perform a policy discovery analysis.

We run 50000 simulation outcomes but we keep only 16024 ones to exclude unreasonable observations that derive from the high dimensional space and range of simultaneously varying parameters. Following Gerst et al. (2013)'s approach, we also use multiple criteria simultaneously to evaluate a policy outcome, without a specific trade-off function since, as the authors argue, there might be disagreement among stakeholders about how different attributes can be collapsed to one metric. We conduct four separate analyses with respect to specific goal and/or combination of goals: *1.* GHG emissions; *2.* Gini index; *3.* GHG emissions and Gini index and *4.* GHG emissions, Gini index and GDP.

Subsequently, we define outcome thresholds for policy relevant cases (Bryant and Lempert 2010). Our approach constitutes a computational thought experiment interested in directions and relative sizes of effects, but does not represent a real world scenario with relevant absolute outcome values. Hence, we chose our thresholds in order to define directions for outcomes, opting for the median, and for comparison to a stricter relative performance the optimal quartile values (lower quartile for GHG and Gini index and highest for GDP).

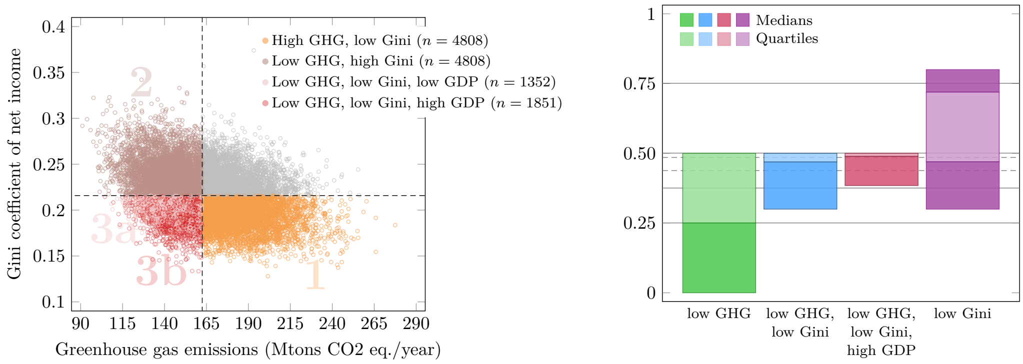
In order to define the importance and the sign of the policy parameter to attain alternative goals, we employ and extend *random forest* machine learning algorithms to the classification problems. Classification trees (e.g. Gerst et al. (2013) referring to Breiman et al. (1984)) use recursive binary splitting procedure to segment or stratify the predictor space (i.e. varying parameters) into areas and subsequently predict the outcome class (i.e. simulation results) in a respective predictor area based on the most prevalent outcome class in that area in the training data (James et al. 2013). Random forests build many unpruned tree models from different training datasets using bootstrapping and average over the prediction results (e.g. for classification problems, predict the prevalent predicted class), reducing variance (James et al. 2013). In addition, to reduce correlation among trees, at each split in each tree only $m \approx \sqrt{p}$, where p reflects the entirety of predictors, randomly drawn predictors can be used (James et al. 2013).

Using stratified sampling we split the observations into 70% training and 30% test datasets. Due to class imbalances, we employ a combination of down sampling of overrepresented classes and creation synthetic observations in underrepresented classes in the training dataset in order to improve model performance. Subsequently, we apply the random forest algorithm to the training data, with $m = 10$, given 107 predictive parameters and with 500 trees in each forest.

4 Results

4.1 The emissions-inequality-GDP nexus

Before considering which policies/parameter values are compatible with the simultaneous curtailment of emissions and inequality, it is necessary to understand how likely the joint achievement of these goals is. Figure 3 plots the final year (2050) values for the net income Gini coefficient and greenhouse gas emissions of all simulations. From the same starting position in 2010, different policies can drive the economy to a wide variety of outcomes. The net Gini coefficient ranges from 0.13 to 0.30, starting from an initial value of 0.23, while the reduction of greenhouse gas emissions is stronger and ubiquitous, falling between 50% and 85% with respect to the initial level of more than 500 Mtons of CO_2 eq. per year.Real GDP varies from 1.25 to 2.25 trillion euros in comparison to its initial value of 1.46, thus including simulations with slightly negative to positive but moderate growth rates on average at the higher bound.[6]



(a) Emissions v. inequality

(b) Actual v. expected-if-uncorrelated outcomes

Figure 3: Panel 3a shows the relation between greenhouse gas emissions and inequality at the end of the simulation run (2050). Each point represents a different simulation. The vertical and horizontal dashed thresholds are the median values calculated over all simulations. Panel 3b reports the percentage of all simulations that reach a certain policy goal or combination of goals; the lighter colours indicate the share of simulations that reach each objective when quartiles (rather than median values) are used as thresholds. The solid and dashed horizontal lines indicate the expected percentage of simulations (calculated using medians and quartiles to define thresholds, respectively) if policy goals were uncorrelated. Note that the observations that reach the low (below-median) GHG objective in Figure 3b are those in quadrants 2, 3a and 3b of Figure 3a; the observations that reach the low Gini objective are those in quadrants 1, 3a and 3b; the observations that reach the low GHG, low Gini objective are those in quadrants 3a and 3b; the observations that reach the low GHG, low Gini, high GDP objecive are those in quadrant 3b.

Panel 3a suggests a trade-off between income distribution and emissions. Hence, it appears that major efforts focusing on de-carbonisation alone could worsen social conditions. However, attempts to offset such trends through economic growth pose a threat to the initial goal of reducing emissions as we also observe a trade-off between GDP and emissions as well as a positive relation between GDP and improvements in income distribution (see figure A.1).

This socioeconomic-environmental trade-off also suggests that the path towards a just transition is somewhat narrow, even though a reasonable number of simulations do reach below median emissions and inequality together. Panel 3b illustrates this idea displaying the decreasing number of simulations that reach multiple goals and comparing them to the number that would be obtained if emissions, income distribution and GDP where uncorrelated. Less than 20% (3203 out of 16024) of the simulations, in the darker blue bar, reach a below median Gini coefficient and emissions. Adding above median GDP to the equation (red bar) leaves us with 9.7% of all simulations. If these three indicators were uncorrelated, we would expect 25% (12.5 %) observations to fall within each group.

The trade-off becomes more restrictive if we consider only the number of simulations on

[6]A yearly rate of growth of about 1.08% between 2010 and 2050 implies a real GDP of 2.25 trillion in 2050. Note that the decreasing population can not explain the differences in GDP because it does not vary across the simulations.

the lowest quartiles for emissions and inequality, highlighted in the lighter color bars of panel (b). Only about 3% ($n = 496$) of all simulations reach the bottom quartile for emissions and inequality together; these are about 50% of what we would expected under no correlation. Additionally considering the top quartile GDP leaves 175 simulations on the light red bar or about 1% compared to an expected 1.5% if all three indicators where orthogonal.

The empirical literature has thus far delivered mixed results on a trade-off between emissions and inequality, while a positive correlation between growth and emissions has been verified more consistently. Both Ravallion et al. (2000) and Rojas-Vallejos and Lastuka (2020), analysing a sample of different countries, find evidence of a trade-off but argue that it is not as strong, in the former, or is not verified, in the latter study, among high income countries. Using a longer sample (1870-2014) for G7 countries, Uddin et al. (2020) provided further evidence of a non-linear relationship. Their study concludes that there was a trade-off only between the 1950s and the end of the 1990s. Finally, Jorgenson et al. (2017) consider the trade-off between U.S. states (1997-2012) and find no correlation between the Gini coefficient and emissions, but do find a positive relation between emissions and the income share of the top 10%. These seem to be in line with our simulation results which, despite tilting in favour of this trade-off do not rule out the joint achievement of these goals under some parameter combinations.

This illustrates how the path towards a just transition becomes narrower if a relatively higher GDP growth is targeted. Thus, singling out growth as a necessary condition to reach a low-carbon transition with improvements in income distribution would lead us to discard about half of the simulations, or policy-mixes, that reach these two goals at lower GDP levels.

These initial results also suggest that a policy path designed to reach a single objective is not neutral with respect to other important goals and might, in fact, compromise their achievement. This calls for a deeper understanding of the policy mixes, or in our case the parameter space, able to balance possibly contrasting forces in the path towards a just transition.

4.2 Main policy variables

Figure 4 reports the results of the random forest analysis in the left panel. It ranks, among all the policy parameters included in the sensitivity analysis, the 10 most important (higher mean decrease in accuracy) predictors for the achievement of the four different goals highlighted in figure 3, on a logarithmic scale. The right panel plots the mean values of the same policy parameters in these simulations, in percentage variation with respect to all $16,024$ simulations performed, which indicates the direction and size of their impact. The distribution of the parameters is presented in figure A.6.

Trade-offs are particularly prevalent between low emissions (circles) and low inequality (squares): most parameters selected only work towards one of these goals and the means of the three appearing for both (exports, output and investment constraint) have opposite signs. Thus, pursuing both goals simultaneously calls for a balanced mix between inequality- and emission-directed policies, which are highlighted in the blue triangles of figure 4. Finally, the 10 most important predictors that also result in higher GDP levels are plotted in the red diamonds.

The factor with the highest relevance for all cases is the expansion of renewable energy supply to fulfill industries' demand. The magnitude of expansion, in figure 4, underlines that if reduction in inequality and higher growth is pursued, obtaining low emissions becomes more challenging and requires a larger deployment of renewables. Renewable energy sources to satisfy households' demand works in the same direction, but are among the most relevant parameters for two of the four cases, mostly because households' energy use and their respective emissions are far lower than those generated in production.

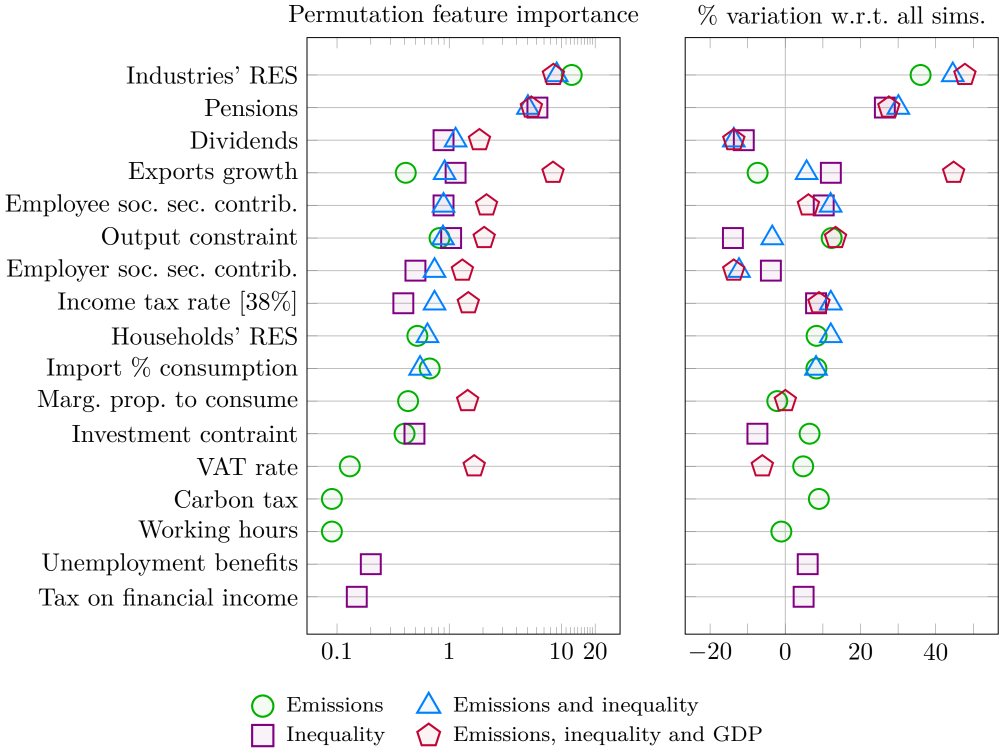


Figure 4: Main policy variables. The two panels provide information on the 10 main policy variables associated with each objective or combination of objectives: emissions (green circles); inequality (violet squares); emissions and inequality (blue triangles; emissions, inequality and GDP (red pentagons). The left-hand panel shows the permutation feature importance of each variable, plotted on a log scale; higher values indicate an important predictor of which 'goal quadrant' is reached by the simulation. The right-hand panel shows the difference between the average value each parameter takes in a certain 'goal quadrant' and the average value in all simulations.

An additional political leverage point towards a just transition is directly addressing income distribution. Here, pensions play an essential role[7]. Higher pensions tend to increase aggregate demand and therewith emissions, but their effect on distribution is likely dominant as most pensioners are located towards lower end of the income distribution with a higher proportion of low skilled with respect to the working age population. Unemployment benefits have a similar role, however, as they are directed at a much smaller portion of the population, their capacity to redistribute income is limited in comparison to pensions. Thus, large direct transfers towards the bottom of the income distribution constitute a promising tool as their capacity to improve distribution compensates for the increase in aggregate demand and its respective emissions.[8]

Another group of parameters points to the potential of addressing the income distribution from the opposite angle, by limiting top incomes. Less dividends, a higher labour income tax in top brackets and, to a lesser extent, a higher tax on financial income, are potentially capable of providing a double dividend: they reduce inequality while simultaneously limiting consumption and consequently emissions.[9] Social security contributions of employees have

[7]The actual parameter considered is the pensions-to-wage ratio which determines gross pensions and a percentage of the mean annual wages of workers employed, by skill level.

[8]The model also incorporates more targeted benefits, for low-skilled individuals out of the labour force (other benefits in appendix X), but due to their small scale, even large variations in their per capita value (±50%) have minimal impacts on the overall income distribution.

[9]Due to the aggregate nature of the groups of individuals in the model most of the high income earners, high-skill employed males and females, top marginal income tax corresponds to the 4^{th} income tax bracket $(28,000 - 55,000$ €/year). Except for the capitalists which constitute only 1% of the total population.

a similar effect, reducing net labour incomes of the employed. Since the employed tend to earn more than individuals of the same gender and skill who are unemployed, retired and out of the labour force, increasing their contributions might reduce inequality.

A third group of parameters suggests a negative relation between investments and inequality. A reduction in employers social security contributions, value added taxes, and of the percentage of profits paid as dividends all tend to boost (retained) profits, allowing industries to finance more investments. The acceleration of fixed capital formation aided by these variables have three main effects on our goals: on income distribution via dividends, on employment and aggregate demand through investments and on technological progress through the renovation of fixed capital which can increase energy efficiency and labour productivity.

The potential to address inequality by increasing aggregate demand (for investment) is also evident through the presence of output and investment constraints in figure 4. The figure suggests that the absence of these constraints in a simulation is important to reach low inequality, while no output constraints is relevant to achieve low emissions and low inequality together. However, if we consider only low emissions (green circles), imposing these constraints and thus limiting production and investments actually contributes to curbing emissions.

Exports play a uniquely relevant role in our results, being the only variables among the 10 most important in all four cases[10]. They represent a strong stimulus to economic growth and, thus, assume below average values in simulations aiming at low emissions only (green circles) while growing above average in those that also reach low inequality (blue triangles) and way above average in those that achieve all three goals (red diamonds). Still, we note that relying on net exports to drive the growth and distribution of national income is not a feasible option at the global scale. The same is true for the increase in the percentage of consumption goods imported, which is identified among the most relevant parameters for low emissions (green circles) and low emissions, low inequality (blue triangles), which is not a surprise as an increase in imports is roughly equivalent to exporting emissions in our model.

Reductions in marginal propensities to consume are also among the most relevant parameters for two of the four categories. Below average consumption is associated with lower emissions and even lower consumption reductions with low emissions, inequality and higher GDP[11].

Finally, our results also identify two policies that are dominant in the current debate and literature on just transition: carbon tax and working time reduction. Small reductions in hours worked are associated with lower emissions, on average, as suggested by most empirical studies (Antal et al. 2020). However, we find no evidence in favour of the double dividend – jointly improving socioeconomic and environmental indicators – often associated with working time reduction in the literature (Fitzgerald et al. 2018).

The carbon tax is also among the most relevant variables for emission reductions in figure 4. Even though recent evidence points to a small effect of carbon taxes over low-carbon innovation (van den Bergh and Savin 2021), the main reason for its moderate impact is likely related to the aggregation level of our model. Production and energy demand are modelled at the industry level, whereas most adjustments from the carbon tax potentially occur within industries imposing a higher burden on heavy polluters.[12] Despite this less prominent role, when compared to most of the environmental economics literature (Metcalf 2019; Hájek et al. 2019), it is listed among the 10 most important out of 107 possible

[10] The parameter included in the sensitivity analysis varies the scale of an exogenous trend in exports. In addition to this, exports also depend on price elasticity which does not figure among the top 10 parameters in the random forest analysis.

[11] Note however that large reductions are unlikely to be drawn due to the form of the distribution chosen for changes in the marginal propensity to consume (see C).

[12] For instance, looking at the electricity sector, while the industry as a whole might feature a relatively low emission intensity, high polluters like coal plants would typically face much higher carbon costs, driving the impact of the tax within the electricity generation industry.

parameters. Moreover, no recycling scheme directly associated with the carbon tax revenue is modelled, which could explain why it does not contribute[13] to reduce inequality as this are often pointed as necessary for a carbon tax to be progressive (Fremstad and Paul 2019; Callan et al. 2009).

Taken in comparison to the literature review, our results emphasise that a transition towards low emissions and low inequality simultaneously calls for a variety of important measures across several policy categories. This distinguishes this study from the most frequent methods by placing it towards the right in the lower panels of figure 1. In particular targeted measures to address the income inequality seem crucial, whereas more diffuse approaches to increase national income in general (e.g. through higher wages or government expenditure) are not as relevant. On the other hand, figure 4 underlines some environmental impacts of socio-economic policies, mainly by limiting top incomes, which appears to be neglected in the reviewed literature, and containing aggregate demand. Therefore, strong distributive policies that avoid to inject too much aggregate demand into the economy provide a key tool towards a just transition, as additional demand tends to require compensation in the form of more and faster deployment of renewable energy sources.

Technological progress, prevalent in the reviewed literature, is notably absent among our relevant parameters. While the energy transition towards renewables certainly implies some technological progress, the innovations explicitly modelled at the macro level – labour productivity, intermediate inputs and energy efficiency – do not appear to play a major role in the path towards a just transition. This meager role of energy efficiency to reduce emissions is likely associated to economy-wide rebound effects (Brockway et al. 2021) in which efficiency gains are partially translated in increased consumption, through lower prices of energy intensive goods, or investments due to the reduction of production costs and increase profit rates.

4.3 Low emissions, low inequality pathways

Some of the most noteworthy results discussed in this section are evident from the drivers of emissions and inequality summarized in figure 5. It plots the dynamics of greenhouse gas reductions (GHG) which are broken down in variations of the GDP, energy intensity of production (NRG) and the emissions intensity of energy demand (EM) in 5a, and the decomposition of the net income Gini coeffiicent (N) between the Gini coefficient of gross income before taxes and transfers (G) and the ratio between the former and the latter.

$$GHG = GDP \cdot \frac{NRG}{GDP} \cdot \frac{GHG}{NRG} \qquad\qquad N = G \cdot \frac{N}{G}$$

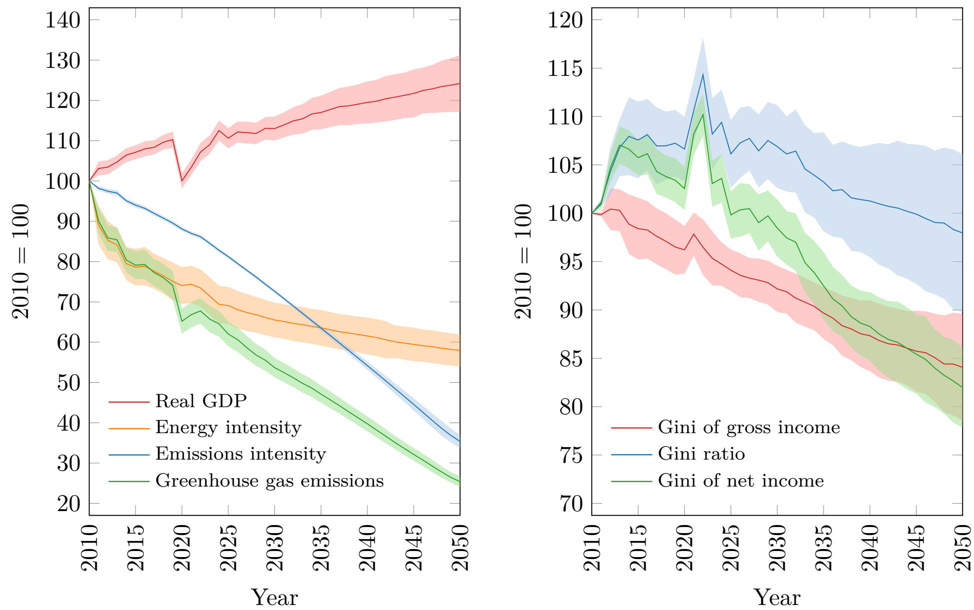
Figure 5 is based on a new set of 500 simulations performed using the same sensitivity variables (C), but imposing the means and standard deviations of the simulations that jointly reached below median emissions and inequality in figure 3. To further highlight the most relevant drivers of these goals, we selected the 11% ($n = 55$) of simulations that end up with both bottom quartile emissions ($\leq 146\, Mtons\, CO_2\, eq./year$) and inequality ($Gini \leq 0.197$)[14].

The dynamics further stress 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 2025 and are less than enough to offset the already modest GDP expansion. Thus, large scale curbing of greenhouse gas emissions depends heavily on the expansion of renewable energy.

Figure 5b illustrates how variations in the Gini coefficient calculated using disposable income are affected by the evolution of market income (labour and financial) and by the capacity of public taxes and transfers, including pensions and unemployment benefits. It

[13] Or contributes less.

[14] These correspond to the bottom quartile of all simulations presented in figure 3



(a) Simplified Kaya identity

(b) Gini coefficient decomposition

Figure 5: Decomposition of greenhouse gas emissions (top-row) and income inequality (bottom-row) for simulations that jointly achieve bottom quartile emissions and inequality. The panels plot the means and one standard deviation confidence intervals. 5a decomposes greenhouse gas emissions in real GDP, Net inland energy consumption divided by GDP (energy intensity) and total emissions divided by net inland energy consumption (emissions intensity). 5b decomposes variations in the net income Gini coefficient (after taxes and transfers) between variations of the gross income one (only labour and financial income) and the ratio between the two.

confirms the role of overall economic activity with employment gains, wages and profits that drive the trend in inequality. However, it also highlights the importance of a more progressive tax and transfer system. The redistribution of income promoted by some of the parameters highlighted in figure 3a such as dividends, income and financial income taxes, pensions and unemployment benefits seem crucial for shifts in the net income Gini coefficient and contribute for its sharper decline after 2030.

The figure also allows us to better understand the trade-off between emissions and inequality highlighted in the beginning of this section. The positive correlation between growth and emissions seems to impose a constraint on the capacity to distribute income through growth without jeopardizing a low-carbon transition. It also points to an asymmetry in distributive policies. Reduce inequality through a faster growth of bottom incomes alone tends to increase consumption and emissions. It can, however, be compensated by policies that restrict income or emissions directly among top earners as increases in energy demand from actual redistribution are small (Oswald et al. 2021).

5 Concluding remarks

The simulation exercise here presented finds a similar number of simulations that are able to combine reductions in greenhouse gas emissions and income inequality with and without above median GDP growth rates. This suggests that pursuing growth is not the only route towards a better distribution of national income amid a low-carbon transition, as often argued or assumed by green growth proponents. Nonetheless, neither does it assert that curbing GDP is necessary to reduce emissions. Still, the results suggest that growth and distribution do require at least some expansion of aggregate demand that must be compensated by an increased pace in the transition from fossil fuel to renewable energy sources.

The policy variables identified as the most relevant show a small intersection between those that drive emissions and income distribution. Thus, in contrast to the majority of studies reviewed in section 2, the joint pursuit of these two goals is likely to require a large number of simultaneous and coherent policies. Moreover, studies focusing on the evaluation of few or single policies risk under- or overestimating the necessary scale of these policies. The deployment of renewables needed to reach emission goals is larger if governments are also increasing public benefits to improve income distribution and limit social opposition to environmental policies.

When jointly considering reduction in emissions and inequality our results select, among the policies directly connected to income distribution, those that either have an ample redistribution potential (focus on lower income groups) and those capable of reducing or containing the growth of top incomes, at the expense of those directly related to aggregate demand expansion such as government expenditure, wage increases and (higher) exports. A notable absence among the selected policies are those directly related to energy efficiency.

Finally, our results suggest that a progressive tax and transfer system able to redistribute income without major increases in GDP is compatible with a just transition. Thus, the trade-off between emissions and inequality, although often present, might actually depend on the kinds of policies enacted to improve income distribution.

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Authorship statement

NC: methodology (model development, programming), investigation (model input data), data curation, formal analysis, visualisation, writing (original draft). *MC:* methodology (model development). *AC:* supervision, conceptualisation, 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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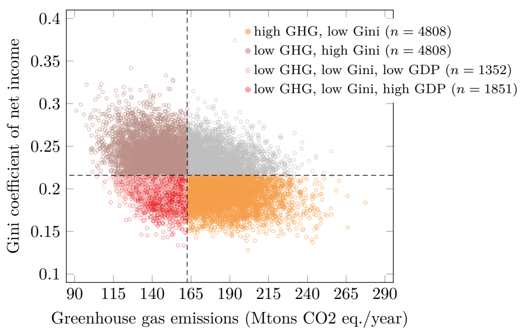
Appendix

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.

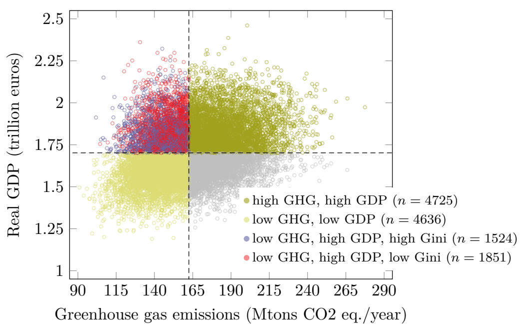
A Additional results

A.1 The emissions-inequality-GDP nexus

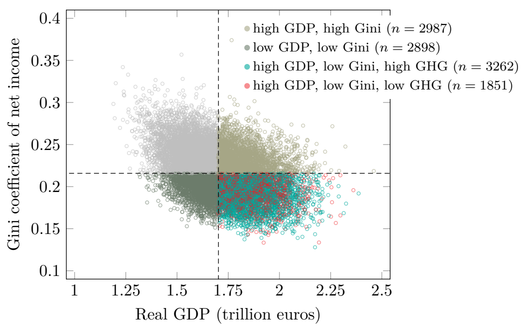
Figure A.1 shows the relationship between greenhouse gas emissions, inequality, and GDP in the final simulation year (2050). Each point represents a different simulation. The vertical and horizontal dashed lines represent the median values calculated over all simulations.



(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 variables 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, which describe how the probability of the desired policy outcome changes with a certain variable of interest, keeping all other variables 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

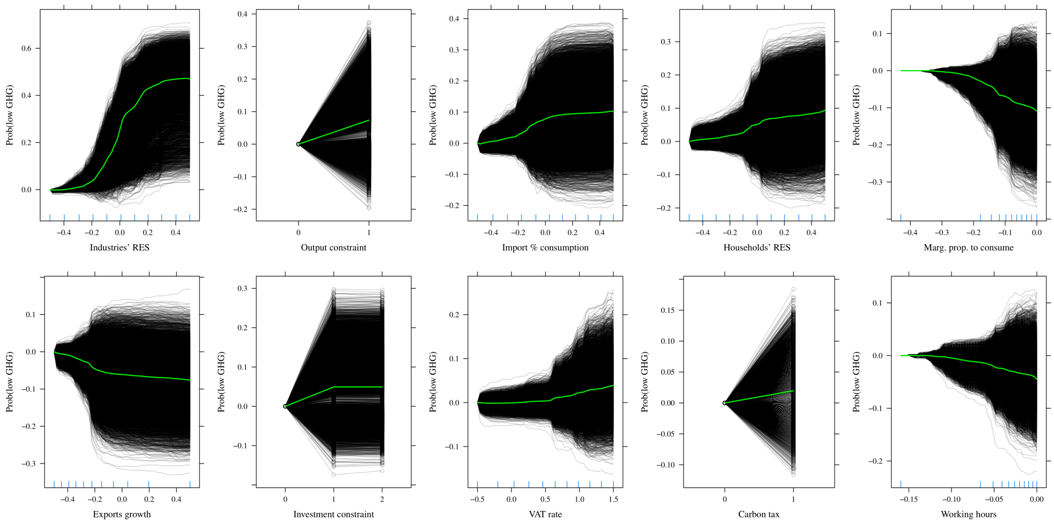


Figure A.2: ICEs and PDP of the 10 main policy variables (policy objective: GHG).

A.2.2 Policy objective: inequality

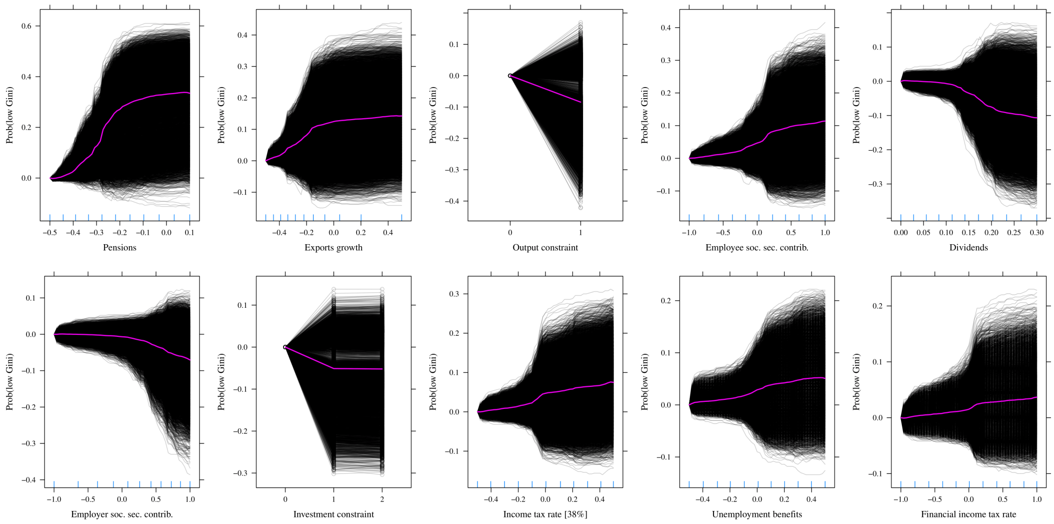


Figure A.3: ICEs and PDP of the 10 main policy variables (policy objective: Gini).

A.2.3 Policy objectives: emissions and inequality

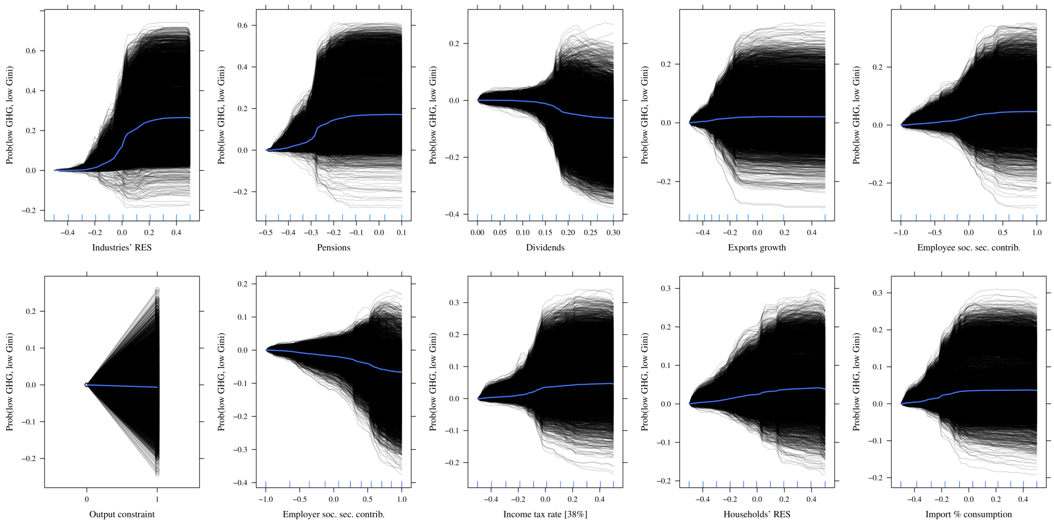


Figure A.4: ICEs and PDP of the 10 main policy variables (policy objectives: GHG and Gini).

A.2.4 Policy objectives: emissions, inequality and GDP

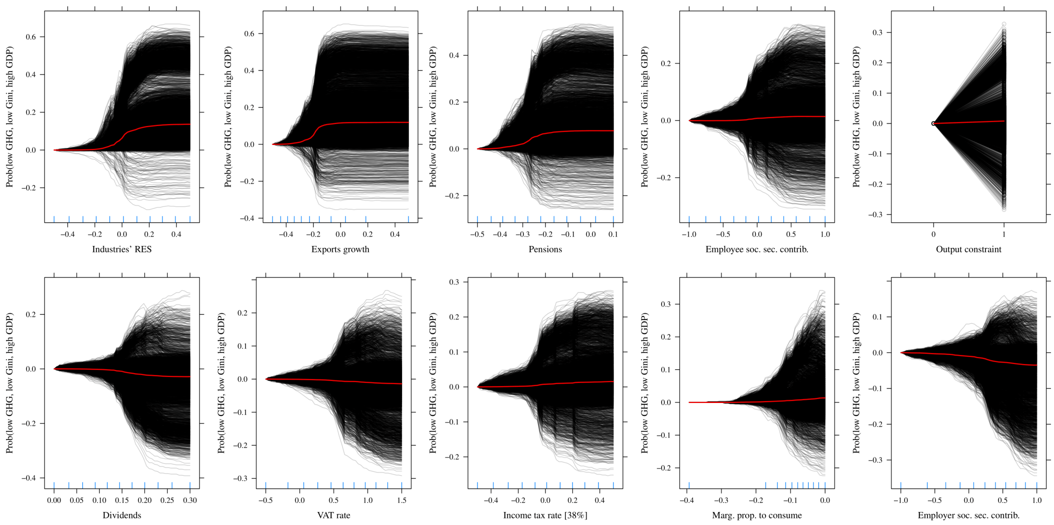


Figure A.5: ICEs and PDP of the 10 main policy variables (policy objectives: GHG, Gini and GDP).

A.3 Kernel densities

Figure A.6 shows the kernel density distribution of the main continuous policy variables. The coloured lines describe the distribution of variables 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 distribution of variables across all simulations. In all cases, 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 random policy variables.

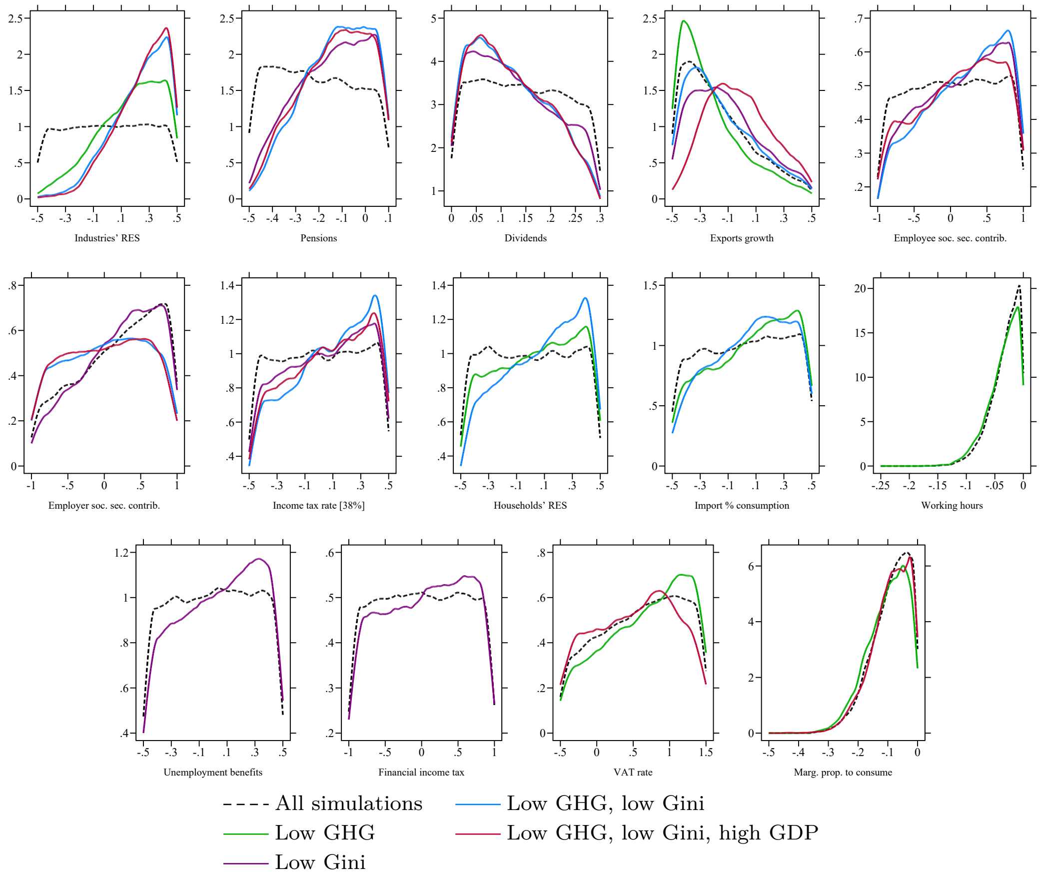


Figure A.6: Kernel density distribution of the 10 main continuous policy variables.

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 algorithm will tend to overlook, and therefore have 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 fitting the model; conversely, the oversampling approach involves 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. This can be done, e.g., by using the Synthetic Minority Oversampling Technique (SMOTE), which 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 standard practice in the machine learning 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 to from 11214 to 11198, i.e. about 2800 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)	5608	-	-	-	-
n (low GHG)	5608	-	-	-	-
n (overall)	11216	-	-	-	-
Objective: Gini					
n (high Gini)	5608	-	-	-	-
n (low Gini)	5608	-	-	-	-
n (overall)	11216	-	-	-	-
Objectives: GHG and Gini					
n (high GHG, high Gini)	2242	2242	3365	3365	2800
n (high GHG, low Gini)	3365	2242	3365	3365	2799
n (low GHG, high Gini)	3365	2242	3365	3365	2799
n (low GHG, low Gini)	2242	2242	3365	3365	2800
n (overall)	11214	8968	13460	13460	11198
Objectives: GHG, Gini and GDP					
n (high GHG, high Gini, high GDP)	1006	952	2323	2322	1700
n (high GHG, high Gini, low GDP)	1215	952	2323	2323	1699
n (high GHG, low Gini, high GDP)	1069	952	2323	2322	1700
n (low GHG, high Gini, high GDP)	2304	952	2323	2322	1699
n (high GHG, low Gini, low GDP)	2323	952	2323	2322	1700
n (low GHG, high Gini, low GDP)	1066	952	2323	2323	1700
n (low GHG, low Gini, high GDP)	1279	952	2323	2322	1699
n (low GHG, low Gini, low GDP)	952	952	2323	2322	1700
n (overall)	11214	7616	18584	18578	13597

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 policy variables 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.7 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 variables for 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 variables 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 model under different resampling methods.

	No resampling	Majority undersampling	Minority oversampling	SMOTE	SMOTE & majority undersampling
Objective: GHG					
Overall accuracy	.830	-	-	-	-
(Accuracy 95% C.I.)	(.819, .8416)				
Sensitivity	.826	-	-	-	-
Specificity	.834	-	-	-	-
Objective: Gini					
Overall accuracy	.811	-	-	-	-
(Accuracy 95% C.I.)	(.799, 0.822)				
Sensitivity	.794	-	-	-	-
Specificity	.826	-	-	-	-
Objectives: GHG and Gini					
Overall accuracy	.672	.647	.671	.658	.652
(Accuracy 95% C.I.)	(.659, .685)	(.633, 660)	(.658, .684)	(.644, .671)	(.638, .665)
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
(Accuracy 95% C.I.)	(.538, .567)	(.505, .534)	(.549, 0.577)	(.531, .559)	(.518, 0.546)
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

C Simulation parameters

Table C.1 lists all parameters that we let vary in the simulations. Based on their characteristics, we grouped them into Structural parameters, Non-calibration parameters, and Calibration parameters.

Each structural parameter determines the functional form of a certain model equation (references to the various equations are given in the last column of Table xxx). For instance, if the Investment constraint parameter takes a value of 0, then no restriction is placed on firms' investment; if it takes a value of 1 then firms must internally finance a fixed proportion of their desired investment expenditures, and if it takes a value of 2 then this proportion becomes a function of firms' leverage. The output constraint parameter indicates whether production is constrained by fixed capital (value 0) or not (value 1). The carbon tax may be activated (value 0) or not (value 1). The warming scenario parameter selects one among

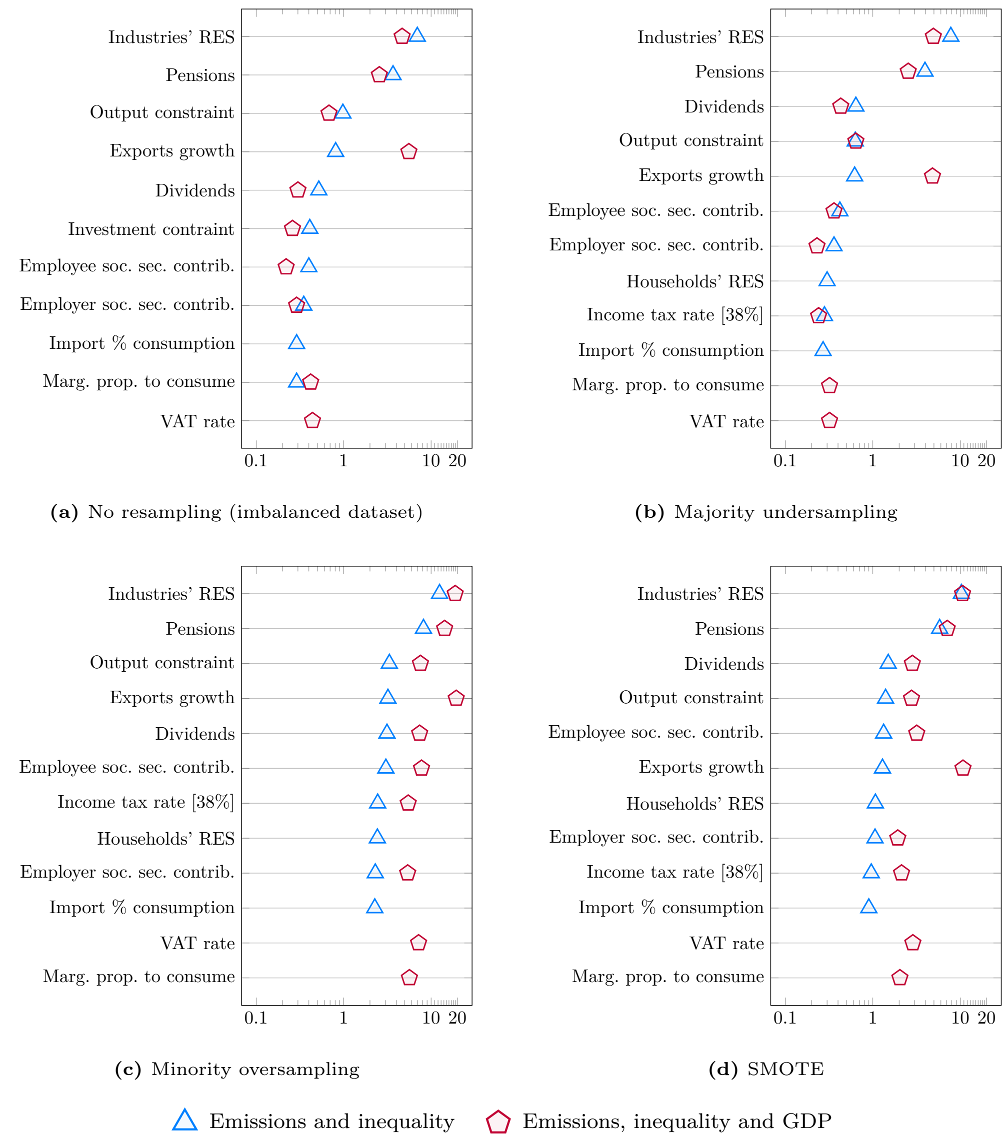


Figure B.7: Permutation feature importance of the 10 main policy variables under different resampling methods.

4 different Representative Concentration Pathways (see Figure 2), which in turn correspond to different temperature projections.

Non-calibration parameters can vary over a wide range of values, which generally spans from −50 percent to 50 percent their initial value. Each of these variables follows a linear trend, starting from the same value in 2022 and reaching the randomly selected value in the final simulation year (2050). For example, if a value of 0.25 is randomly drawn for the Depreciation rate parameter, then the depreciation rate of fixed capital will remain fixed between 2010 and 2022 in all industries, and then increase linearly up to 25 percent above its initial level by the end of the simulation run.

Finally, the Calibration parameters group includes the main parameters for which the model was calibrated. Since these parameters were calibrated to actual data, they can vary over a smaller range of values than do Non-calibration parameters. Moreover, values are determined in the first period and then remain fixed throughout the simulation run. The letter i within parentheses indicates that an independent random draw is made from the same distribution for each industry featured in the model. Thus, for example, the sensitivity of desired 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 the 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						
Max. investment	{0,1,2}	0	2	vector	2	2.27
Full capacity	{0,1}	0	1	vector	1	2.4'
Carbon tax	{0,1}	0	1	vector	0	2.91
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 consumer spending	%	-0.5	+0.5	continuous uniform	0	2.7
Import share of government spending	%	-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	2.145-148
Industries' RES growth rate	%	-0.5	+0.5	continuous uniform	0	2.145-147
Δ Technical coefficients	%	-0.5	+0.5	continuous uniform	0	
Δ Labour productivity	%	-0.5	+0.5	continuous uniform	0	
Financial tax[15]	%	-1	+1	continuous uniform	0	2.85
Employee social security contrib.[16]	%	-1	+1	continuous uniform	0	2.77
Employer social security contrib.[17]	%	-1	+1	continuous uniform	0	2.78
VAT rate[18]	%	-0.5	+1.5	continuous uniform	0	2.87
Corporate income tax rate[19]	%	-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[20]	%	-0.5	+0.5	continuous uniform	0	2.93
Pension to wage ratio[21]	%	-0.5	+0.1	continuous uniform	0	2.96
Sickness and disability benefits	%	-0.5	+0.5	continuous uniform	0	exogenous
Family and children benefits	%	-0.5	+0.5	continuous uniform	0	2.98
Other benefits	%	-0.5	+0.5	continuous uniform	0	exogenous
Income tax rate [0.23]	%	-0.5	+0.5	continuous uniform	0	2.83

[15] https://tinyurl.com/3k6nfjkd
[16] https://tinyurl.com/v9szn9kv
[17] https://tinyurl.com/334mc44v
[18] https://tinyurl.com/5k9j9cac
[19] https://tinyurl.com/ufvztxph
[20] https://tinyurl.com/ymyu3xu7
[21] https://tinyurl.com/mez7354w

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	2.91
Calibration parameters						
Tech. probability sens.		9	15	continuous uniform	11.93	2.13-14
Initial prob. T2	%	0.35	0.75	continuous uniform	0.67	2.13
Initial prob. T3	%	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
ω employment		0.35	0.55	continuous uniform	0.45	2.73
ω lab. productivity		0.7	1	continuous uniform	0.99	2.73
ω 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 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.