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Beyond the Energy System: Modeling Frameworks Depicting Distributional Impacts for Interdisciplinary Policy Analysis

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Since the signing of the 2030 Agenda for Sustainable Development by the United Nations Member States and the Yellow vest movement, it is clear that emission-reducing policies should consider their distributional impacts to ensure a sustainable and equitable growth compatible with the Paris Agreement goals. To this end, the design of environmental and energy policies should be accompanied by an interdisciplinary analysis that includes potential effects on distinct groups of society (defined by income, age, or location), regions, and sectors. This work synthesizes common modeling frameworks used to assess technical, socio-economic, and environmental aspects in policy analysis and the recent progress to portray distributional impacts in each of them. Furthermore, the main indicators produced by each method are highlighted and a critical review pointing to gaps and limitations that could be addressed by future research is presented.

1. Introduction

The consideration of distributional impacts in the analysis of the energy and environmental policies has risen in importance as more ambitious climate policies are implemented worldwide, often imposing taxation on energy products. Distributional impacts refer to the case when different household groups or individuals are affected by a policy to a different degree. Distributional impacts are commonly associated with inequality which may include differences in the environmental burden or distribution of income and welfare. A case that illustrates the negative consequences of not considering the distributional effects of climate policies is the Yellow vest movement that started in 2018 in France. The movement was marked by mass protests against the rising fuel taxes and prices and claimed that middle and working classes were paying a disproportionate share of the burden from the national tax reforms.[1] These protests are a sign of how the issue of inequality has grown in relevance in recent years and how neglecting this topic may hinder climate protection action. In the European Union, for instance, increasing levels of income and carbon inequality in a large number of Member States are causing concerns for both the sustainability of economic growth and social cohesion.[2] Globally, the gap between rich and poor is increasing and in 2015 the wealth of the richest 62 people in the world was equal to that of the bottom half.[3]

To tackle the issue of inequality, the United Nations adopted in 2015 the 2030 Agenda for Sustainable Development, in which reducing economic disparities is one of the seventeen sustainable development goals (SDGs).[4] This agreement reinforces the need to provide a global solution for the problem of inequality and shows that policies aiming at sustainable development should consider their social and distributional impacts on different income classes and regions.

To this end, this work reviews the recent literature on the model-based methods utilized for policy analyses in the areas

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of economics, energy systems, and environmental damages. Furthermore, we explore ways in which these models and methodologies depict distributional impacts, the main indicators obtained from their results, shortcomings of each modeling methodology, and suggest improvements for future research.

2. Distributional Impacts from Energy and Environmental Policies

This section provides a short literature overview of possible distributional impacts of different environmental policies. As the literature on environmental policies and distributional effects is vast, we focus here on the main reasons why distributional impacts may occur and their relevance for environmental policy assessment.

Depending on the chosen policy instrument and the underlying socio-economic structure, distributional impacts of environmental policies may vary significantly, both between countries and within countries.[5–7] Overall, environmental policies are usually associated with regressive distributional impacts in literature, disproportionately affecting disadvantaged population groups. There is, however, also evidence for progressive impacts, especially in developing countries, where inequalities can be effectively reduced.[7,8] The focus and significance of distributional impacts vary depending on the unit of analysis, i.e., the spatial scale of the study, the chosen indicator(s) concerning inequalities considered, and sectors/goods affected.[7] For a detailed discussion of possible distributional impacts of individual policies, the reader may refer to refs. [7,8].

Evaluating distributional impacts of environmental policies should consider both financial implications, i.e., impacts on income and wealth distribution, and possible environmental benefits in the form of reduced environmental hazards or improved accessibility to environmental goods.[8] The latter is, however, difficult to assess quantitatively and may vary greatly on a geographic scale. In addition, the relationship between a lower socio-economic status and higher exposure to environmental hazards is ubiquitous, especially within countries.[8,9] Thus, assessments of distributional impacts of energy and climate policies often concentrate on income distribution, neglecting possible benefits from reduced environmental inequalities or other indirect effects. Financial implications usually depend on the demand elasticities of the affected goods and possible budget or credit constraints associated with socio-economic status, e.g., different disposable income, owned assets, or accessibility to technologies.[7] Depending on how the policy is funded and on who consumes the affected goods, distributional effects may impact households, industries, or states both negatively or positively. Well-designed strategies may also achieve progressive outcomes by considering appropriate compensation schemes, either by increasing household income through lump-sum payments or reducing other taxes, or by public investments, e.g., in infrastructure, or through the social security system.[5,7,8]

As distributional impacts of environmental policies depend significantly on the policy design itself, and at least partially on the geographic distribution of environmental burdens,[7] it is only possible to assess them on a case-by-case basis. Ignoring possible distributional effects may, however, result in less effective policies and even increased inequalities due to missing policies to mitigate potential impacts.[5,7,8] These are, however, often only included on a broader level in policy impact assessments without any detailed analysis of how different socio-economic groups are affected.[10] Existing policy impact assessment guidelines often only state that some social and environmental impact assessment should be conducted[11] and offer scope for interpretation regarding the depth of analysis and applied methodologies. Such contextual factors flow into the model design, which often ignores the complexity of distributional impacts by focusing predominantly on economic efficiency instead of equity.[5]

3. Quantitative Methods and Modeling Frameworks Dealing with Distributional Impacts

This section briefly introduces modeling frameworks linked to the analysis of the energy and climate policies and how they portray distributional impacts. However, as the utilization of these frameworks precedes the study of environmental policies in its modern transdisciplinary concept, each method alone is only capable of capturing specific effects associated with the measures mentioned earlier.

3.1. Energy System Models (Partial Equilibrium)

Energy system models based on a partial equilibrium framework consider the economic activities of the energy sector or parts thereof. They, therefore, do not consider the implications of energy-related investments on other parts of the economy, e.g., labor or other investment requirements, in contrast to general equilibrium models.[12] The framework can be further categorized into simulation and optimization methodologies (such as PRIMES and the TIMES framework).[13,14] Optimization models aim to identify the least-cost solution and simulation models aim to replicate the development of a specific sector, accounting for the decision making of different actors. The general objective function of the optimization models relies on linear programming and minimizes the discounted total energy system costs, subject to various constraints (e.g., energy or emission balances, efficiency relationships, utilization constraints, reserve capacity, greenhouse gas mitigation targets, emissions, renewable quotas, etc.) as described in equations of S1, Supporting Information.[13]

The techno-economic framework of the partial equilibrium models is typically applied to study the long-term effects of a transition to a low-carbon economy yet often does not include consideration for distributional impacts.[15] Distributional impacts have typically been assessed through linking with other models, e.g., macroeconomic, or by increasing the level of detail in a sector through disaggregation.

3.2. Input–Output Models

Input–output models (IOMs) depict the interdependencies between different sectors of the economy. This framework illustrates how the output from one economic sector becomes the input for another sector and, thus, can cover direct and indirect price changes of different product categories.[6] The indirect impact of carbon taxation policies accounts for higher prices of goods and services using carbon-intensive inputs. This approach commonly assumes that levies are fully passed through to the final consumers. The assumption of inelastic demand corresponds to the short-term incidence of higher prices.[16–19]

As these models have a bottom-up representation of the economy, they are capable of producing results on a regional level, such as changes in sectoral prices and production levels. In terms of distributional indicators with a focus on households, the models can provide changes in income and consumption induced by policies for representative households.

3.3. Macroeconomic Models (General Equilibrium)

Based on the input–output framework, multi-sectoral Computable General Equilibrium (CGE) models are powerful modeling tools to consistently assess the impacts of climate policies in different households. These models link the macroeconomic impacts from changes in prices, assets, and productivity and capture all sources of income, consumption preferences, and skill endowments of households. However, analyzing the implications of climate policies for poverty and income distribution requires that such models explicitly represent different household groups and their heterogeneity in terms of: 1) factor endowments, such as differences in financial assets or labor and skills supply across households; 2) preferences and savings, commonly achieved by differentiating parameters in households' utility functions (e.g., preference shares, substitution elasticities) to simulate different decisions of household types on saving versus consuming; 3) wage rates and different return rates to capital for different households (e.g., imperfect capital markets such as credit rationing according to income), but also household decisions on participation in the labor market depending on their specific characteristics.

An overview of the mathematical formulation of CGE models is given in Equation S2, S3, and S4, Supporting Information.

3.4. Environmental Models

Environmental models are primarily used to estimate the possible environmental impacts of technologies and policies. Environmental impact assessment is conducted regularly as part of a standard policy assessment to avoid any unwanted side effects and identify effective and efficient environmental protection strategies. The applied simulation models often follow the Impact Pathway Approach to relate socio-economic activities to possible environmental outcomes.[20] Due to the involved complexity and variety of potential environmental issues, a myriad of models exists, focusing on different impact categories, geographic scales, and sectors as potential polluters. In contrast to economic models, environmental ones do not focus on financial implications, but try to capture possible impacts of policies on inequalities regarding the exposure to environmental hazards, which may not be possible to be reflected in monetary terms.[8] Depending on their setup and chosen methodology, environmental models may be used to assess distributional impacts of policies on different spatial resolutions and across sectors, population groups, or individuals.

3.5. Microsimulation

Microsimulation models account for behavioral changes by considering consumer choices.[6] In this framework, consumers maximize their utility for a given set of preferences, prices and budgets, while considering their demand to be elastic. Commonly used methods include the Almost Ideal Demand Systems (AIDS),[21–23] the Quadratic Almost Ideal Demand System (QUAIDS),[24–26] the more recent Exact Affine Stone Index (EASI) demand system,[27,28] and the Engel curve model.[29]

These models are capable of assessing policy effects on each modeled household, which can easily be as numerous as the number of respondents in national household surveys.[30] These effects include tax incidence, changes in consumption, and income level. In addition, they are also used to produce estimations on the levels of (energy) poverty as a result of the policy being analyzed.

Despite focusing on individual level modeling, as in agent-based models (ABMs), microsimulation models produce a rich detailed data description of individual behaviors while often lacking the interaction and feedback among individuals.[31] On the other hand, ABMs seek to analyze the interaction and feedback between individuals and how it affects their behavior.

4. Distributional Impacts in Individual Modeling Frameworks

This section discusses in more detail the methods, data requirements, advantages, and limitations of the three main modeling frameworks: partial equilibrium, macroeconomic, and environmental impact assessment models.

4.1. Energy System Models (Partial Equilibrium)

This section describes how distributional effects are traditionally considered in specific partial equilibrium energy system models. The review explores different modeling research by geographic scope, policies evaluated, sectors or actors modeled, and the methods used to incorporate consideration for distributional impacts. This is followed by an assessment of the strengths and weaknesses of different methods and their overall effectiveness in capturing distributional impacts. Various indicators are used to measure the distributional impacts. This section concludes with an overview of the usefulness of this type of modeling framework for assessing the distributional effects of climate policies.

4.1.1. Methodologies to Assess Distributional Impacts of Energy and Climate Policies

Partial equilibrium analyses based on an optimization modeling framework aim to identify the least-cost pathway and the development of technology diffusion under policy targets across the whole energy system. The framework aims to balance prices and quantities across one or more markets to the point of equilibrium between energy supply and demand. Concerning distributional impacts, a key limitation of this methodology is that it only considers what occurs within the energy system boundaries.

Consequently, there is no inherent feedback loop to better estimate the impacts on the broader economy, e.g., increased energy costs, or the collection and distribution of carbon taxes. A second issue concerns the focus of such a framework on technological and economic factors, where the primary objective is to identify longer-term technology pathways toward achieving specific policy targets with limited focus on the role of policy design in the near term and sectoral implications of policy interventions. A more aggregate representation of sectors means that socio-economic differences within sectors are not often represented. A third issue is the optimization paradigm. This approach strongly favors the economic efficiency of a solution with less appreciation of the inertia and barriers inherent across different sectors, and differences between actors. Given their techno-economic focus, the simplification of behavioral representation, and the long-term analytical time frame, such models are less able to simulate the impacts of sector-specific policies, and their distributional impacts.[15,32]

Sabio et al.[33] conducted a review to assess the potential of long-term energy system models to address the distributional impact deficit. This study reinforces the point that traditionally, the impacts on households are difficult to be determined with the standard partial equilibrium model structure for the reasons listed earlier, but particularly noting the issue of aggregation to "typical" households. For the residential sector as an example, this means a focus on disaggregation based on physical building stock but without reference to heterogeneity across individuals, groups, or households. As a result, the differentiated impacts on this heterogeneous sector are negated.

In rethinking how such models could be used for distributional impact analysis, the objective would be to capture insights to determine the impact on economic dimensions (e.g., cost distribution), social dimensions (e.g., well-being, energy welfare), and the overall impact on marginalized and vulnerable groups.[34] As per Sabio et al.,[33] two approaches are considered for the assessment of distributional impacts using partial equilibrium models, namely, disaggregation and linking sector models. A third approach includes off-model interpretation of scenario metrics to understand distributional impacts using complementary datasets, referred to as an equity evaluation.

Model Disaggregation: This approach allows for the explicit definition and consideration of particular socio-economic groups according to their specific circumstances (income, building, tenure, number of people, etc.) within the model framework.[35] The additional heterogeneity in the model provides a basis to assess the differentiated impacts on different groups within a sector.[15] Including disaggregation has become more common in partial equilibrium models as a means to gaining more insight into the behavioral aspects of investment and consumption, but without necessarily focusing on determining the distributional impacts of policies.[36–38] The TIMES–GEECO model applied to Gauteng in South Africa used disaggregation to better reflect the heterogeneity of the household sector by socio-economic factors—and, therefore, the ability of different groups to comply to energy and climate policies.[36,39] A similar approach is applied in the developed country context, where households are disaggregated by various parameters, including socio-economic characteristics around income, building type, tenure.[39,40] The TIMES Actors Model (TAM)-household sector model not only includes the disaggregation of different socio-economic profiles of households but also uses this structure to evaluate the impact of different carbon taxes.[39] However, as this approach is not coupled with a macroeconomic model, the impacts reflect only partially the cost implications of policies on a specific actor, household, or sector. Doda and Fankhauser[41] applied a deterministic partial equilibrium model to assess the often-neglected distributional impacts of climate policies on the supply side. The policy instruments evaluated include emission reduction policies on power suppliers, such as carbon pricing, taxes and subsidies, which also investigate subsidy schemes and their impact on household welfare for specific technologies.

Linking Sector Models: A second approach for incorporating distributional impacts into energy system models is via linking sector models. The benefit of linking is that the energy system model does not have to be disaggregated but can retain its current structure and link to another model such as a CGE (to assess wider economic impacts) or micro-simulation model for detailed sectoral analysis. The process of linking sector models is done either through coupling, soft-linking, or hard-linking. Coupling involves running models separately and exchanging key variables such as energy prices and demands to reach equilibrium. Soft-linking includes the use of an intermediary model or an exchange of common parameters. Hard-linking entails integrating one model into another and demands a high level of modeling skills and reformulation of the model objectives, source code, and underlying database.[42] The types of models commonly linked to the partial equilibrium models include general equilibrium models, micro models, and other economic models, as discussed in Section 5.2.

Equity Evaluation: The third method works with partial equilibrium models as structured, but incorporates consideration of distributional impacts in the scenario definition process and/or undertakes analysis on the model result metrics through the use of complementary datasets, i.e., interprets scenario results through distributional impacts lenses. On the scenario definition approach, Chapman and Pambudi[43] apply a mixed-methods approach, which involves identifying preferences and social equity variables from surveys and then defining scenarios to be evaluated through energy system modeling. The results are then analyzed according to weighted factors for sustainability and social equity.

On the post-processing approach,[34] propose the InVEST approach to estimate the vulnerability of different regions and groups from different low-carbon pathways quantified through the TIMES PanEU model. This analysis first mapped out subnational regions using metrics to capture vulnerability under a low carbon transition, e.g., regions with higher levels of energy poverty, regions dependent on energy-intensive industries and/or hydrocarbon extraction. Based on the regional picture of vulnerability, the next step was to consider how different low-carbon pathways might impact on such regions and communities if such vulnerabilities were to persist in the future.

Various studies have used methods such as model linking and disaggregation, but few have applied them to address distributional impacts specifically through a partial equilibrium energy system model. The strengths and weaknesses of these methodologies in relation to distributional impact analysis are summarized in **Table 1**.

Table 1. Comparison of common modeling approaches to assess distributional impacts in partial equilibrium energy system models.

Method		Strengths	Weaknesses
Model disaggregation		Allows greater detail in representative groups; Explicitly defines and considers particular socio-economic groups according to their specific circumstances	Data-intensive, data availability, long-term data projections, model complexity, and run-time increased
Linking sector models	Coupling	Requires moderate skill level and less detailed knowledge of separate models; Model algorithms and formulation remain unchanged	Direct link between the models needed via variables; Iterations may result in higher computational times and prove more arduous depending on the number of variables exchanged
	Soft-linking	Requires moderate skill level and intermediate model knowledge; Model algorithms and formulation remain unchanged; Makes use of the tool's capabilities	Data analysis is intensive to determine the level of harmonization required. Medium tool development time.
	Hard-linking	Requires high skill level and knowledge of model; Model reformulation required (and development of new source code) Full exploitation of tool strengths	Intensive model analysis and harmonization High tool development time All possible communication channels need to be joined and harmonized.
Equity evaluation		A flexible framework, which allows all other models used to maintain their structure	Data and assumptions can be intensive or scarce Does not capture the complex interlinkages among actors and sectors, such as in the hard-linking method

Data, Metrics, and Limitations: The model disaggregation approach requires additional datasets for capturing differences between households in the model, with a focus on socio-economic factors and their linkage to the energy system, e.g., how much energy they consume, age of appliances and building envelope, household condition, dwelling ownership, access to personal mobility.[15] The challenge is that this approach is very data-intensive. Furthermore, often socio-economic datasets are not linked to the physical energy system. For example, understanding the dwelling profiles in a model by socio-economic category is often challenging due to limited data. A further challenge concerns how socio-economic factors may change over time. This issue can be handled by exploring alternative scenarios. Finally, the data required are dependent on the specific distributional impact question. Distributional impacts are related to many different socio-economic variables. A particular challenge for partial equilibrium models concerns spatial resolution, and therefore exploring regional differences would be problematic. A key question is balance; these models answer different questions and therefore ensuring tractability while building in distributional impact analysis capability is critical.

Fell et al.[15] undertook a useful exercise to ask stakeholders about the utility of such an approach. There was a pragmatic recognition that such models would never be able to capture all issues related to distributional impacts and that large uncertainty would exist when applied to long-term analysis. Although the approach was considered to have potential, stakeholders suggested to focus not only on identifying distributional impacts but could also provide policy insights around different pathways. Key challenges remain for this approach around data—and the suitability of the framework for this type of analysis. However, this should be balanced against the importance of ensuring that distributional impact analysis is recognized in long-term pathway analysis.

The linking approach essentially allows for separate models to exchange data and information between each other. Linkages to CGE models are fairly well understood, whereby energy cost increases are fed from the partial equilibrium model to the CGE model, with feedback in respect of energy demand levels. Linkages to micro-simulation could involve metrics such as energy costs, carbon prices, and energy demand levels, providing the boundary conditions for the sector-level assessment. A key challenge is the consistency between models and the level of complexity in moving toward a hard-linked framework.

Finally, on the equity evaluation approach, Pye et al.[34] provide insights into the metrics used from the partial equilibrium model to further explore vulnerability and distributional impacts. These focused on the energy cost burden on different industries and households under different scenarios, and the levels of investment needed. Both metrics highlight positive and negative impacts, and the requirements for policy interventions. In terms of vulnerability indicators on which to map the scenario metrics, these include energy intensity of industries, energy poverty levels, and employment in carbon-exposed industries. For example, statistical indicators around vulnerability in households aimed at assessing the level of energy poverty show a household or region is already vulnerable to energy cost changes as exemplified in **Figure 1**. The expenditure not only varies widely by regions but also within a region by income group.

The metrics give an indication of whether households would be disproportionately burdened when looking at the required per-household investment costs resulting from the model for a specific scenario. These insights mainly point toward the types of technologies that will be required and give insights to the policy interventions that will be needed to avoid potential detrimental impacts on vulnerable households, industries, or regions—depending on the geographical or sector scope of the model.

Final Remarks: Energy system models are limited by the lack of behavioral representation, including heterogeneous actors and the lack of linkage to the wider economy. Although there is a live debate as to whether such models should be applied to distributional impact analysis, a number of approaches do offer some possibilities. These include further disaggregation of energy models to capture the heterogeneity of households, linking to more detailed sector models, and finally additional interpretation

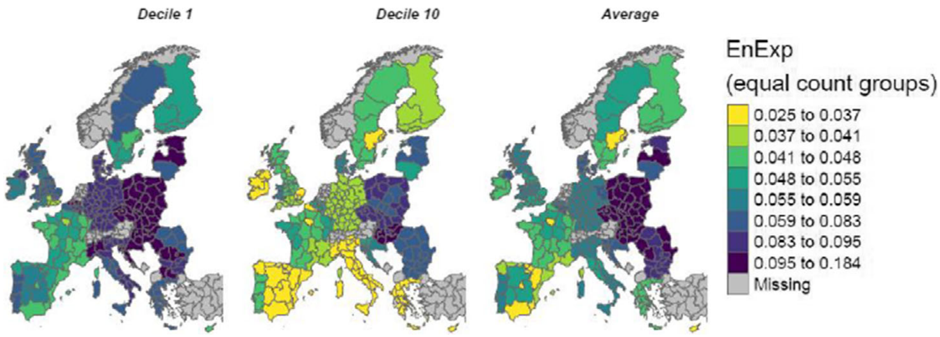

Figure 1. Average household expenditure on energy by income decile (lowest, highest, and average) by NUTS1 regions across Europe. Adapted with permission.[34] Copyright 2019, EC, REEEM project.

of model outputs based on a careful definition of scenarios with relevant indicators. Without further research into the prospects of such approaches, the analyses by energy system models risk ignoring critical issues of equity of transitions and the distributional impacts that arise. Given that such issues are fundamental to a successful low carbon transition, more research on the merits of these approaches are needed.

4.2. Macroeconomic Models

This section reviews methods to depict distributional impacts in macroeconomic models based on the general equilibrium theory. We start by giving an overview of macroeconomic modeling applied to evaluate the distributional effects of energy transition and summarize commonly used techniques to portray these effects in the general equilibrium framework. The description of each technique is followed by a critical assessment of its data requirements, strengths, and weaknesses. Despite not being the focus of this work, but given their importance, the last part of this section briefly comments on the application of IOMs for the analysis of distributional impacts.

The main advantage of using macroeconomic models, compared to energy system models portrayed in the last section, is that general equilibrium models can represent the entire economy. This feature allows for feedback effects between the energy system and other sectors of the economy.

Introducing household heterogeneity into CGE models for the analysis of distributional effects dates back to the 1970s when Adelman and Robinson analyzed income distribution policies in South Korea as a case study.[44,45] The addition of this feature better reflects the fact that households have distinct utility functions, labor types (skilled/unskilled), capital endowments, and consumption patterns and allows for the analysis of socio-economic effects such as poverty, income distribution, the incidence of taxes, and social equity.

In recent years, macroeconomic models are being utilized to depict distributional effects due to their flexible formulation, which allows for an efficient implementation of household heterogeneity. This feature was applied in global models[46–48] by characterizing a representative household on the basis of underlying changes in age, household size, or urban–rural status, to analyze the effects of demographic change on economic growth, energy use and emissions. The inclusion of multiple household groups in global models can be performed by extending the number of household types for several countries or by performing a sequential microsimulation.[49,50]

Most of the methods to integrate income distribution in general equilibrium models have been developed in the context of development economics.[51–53] However, this strand of literature mostly uses static CGE models and analyzes short-term poverty impacts of development-related policy shocks and does not account for several factors that are relevant for long-term climate policy assessment such as education and productivity development.

4.2.1. Direct Modeling of the Income Distribution

This methodology, as shown in **Figure 2**, utilizes a predefined relative income distribution function to describe the income heterogeneity within one or more representative households and can be used to assess the changes in income for different households and number of people or households in risk of poverty. As shown by Boccanfuso,[54] this function can be modeled according to an existing distribution function (e.g., log-normal and gamma), or fit to a specific distribution data, such as household survey data.[30]

Although this method is rarely utilized for climate policy analysis, Van der Mensbrugghe[55] used it to assess the long-term

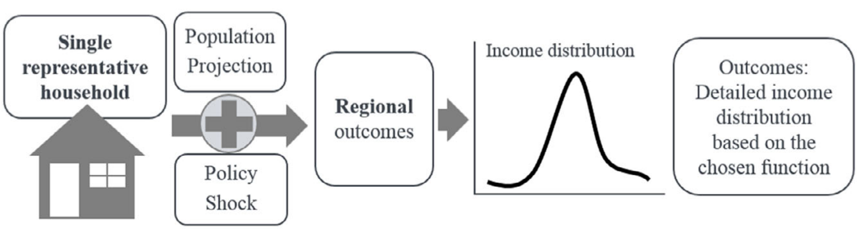

Figure 2. Schematic representation of direct modeling of income distribution. By the authors.

effects on the income distribution of the Shared Socio-economic Pathways (SSP), which are extensively used for climate policy assessment.

Groot and Oostveen[56] analyze the effects of energy subsidy reforms on welfare in selected countries by assuming income to be log-normally distributed. Results indicate that eliminating subsidies yields more budget-saving than the cost of compensating the population for the price increase. Also, countries that currently apply energy subsidization schemes could benefit from reforming them.

Data Issues: As this method focuses on the distribution of income, the data requirements are lower than other approaches. In addition, from an income-level survey, it is possible to derive the parameters for the probability distribution functions.[54]

Limitations: The results of this method depend strongly on the quality of the utilized income data and income distribution, especially considering the tails of the sample (richest and poorest households). In addition, the distribution function is often kept constant over time. Although this effect is negligible for short-term analysis, it should be considered for long-term studies when distribution functions can change significantly.[30]

4.2.2. Representative Households

In this methodology, as shown in **Figure 3**, the number of households is extended from a single representative household (used in conventional CGEs) into several representative household groups. Each group is individually described to account for heterogeneity in aspects such as labor supply, capital endowment, and consumption preferences. This strategy maintains the structure of the CGE model relatively unchanged, except for the increased number of households that are modeled integrally in the CGE framework. The model then produces specific results for each household group in terms of income development, tax incidence, savings, and consumption. The number of representative households can vary from a few to a couple of thousands and the choice of the number depends on computational, data, or application-specific considerations.[30]

Feng et al.[19] divide the household sector into income deciles to analyze the distributional effects of carbon taxation and four revenue recycling options in Taiwan. When compared to the case of no-carbon taxation, using tax revenues to reduce labor taxes resulted in an increase of 1.3% of GDP in 2050, not recycling the revenues led to a GDP reduction of 0.2% and direct redistribution to households with a higher share to low-income earners reduced GDP by 0.1%. On the other hand, the latter option produces the highest reduction in inequality.

Orlov[57] investigates the distributional effects of eliminating subsidy on gas consumption in Russia using a dynamic, multi-region, multi-sector CGE model with the electricity sector disaggregated into key technologies and ten representative household groups (i.e., income deciles). This work suggests that using the additional revenue from higher domestic gas prices can alleviate income inequality in Russia and increase the total private consumption of the poorest decile by 3%. However, the most efficient revenue-recycling scheme is to invest in the energy efficiency of buildings, which have the largest energy-saving potential in Russia, leading to higher reductions of GHG emissions while increasing the consumption of the poorest decile by 1%.

Cunha Montenegro et al.[58] use a multiregional recursive-dynamic CGE model to analyze the impacts of long-term cap-and-trade policies on the EU Member States among four scenarios with different levels of decarbonization. The households of the EU-MS are divided into income quintiles and the revenues from the cap-and-trade policies are redistributed to the households in the same proportion that it occurred in the base year of 2011. Results indicate that increasing the reduction targets in the EU leads to a higher increase of income in low-income households compared with high-income households. However, the magnitude of income distribution varies per Member States.

Rausch et al.[59] used a static CGE model for the US that includes 15 588 household types, to analyze the impacts of a 20 USD/tCO2 carbon price under three different revenue recycling scenarios. They found that the variation in impacts within broad socio-economic groups may swamp the average variation across groups, highlighting the relevance of including household heterogeneity in climate research.

Data Issues: As stated by van Ruijven et al.,[30] a relevant issue to this method is that data concerning consumption, assets, and incomes of households can deviate considerably between household survey data and national accounts. For that reason, it is necessary to reconcile data obtained from household surveys with national social accounting matrices (SAM), on which CGE models are usually based.

For dynamic model runs, one should also consider the development of each representative household with time. As time passes, the composition of education level within each group changes, there is migration among regions, the population structure changes, and fiscal policies adapt to the demography of the population. These phenomena require their own set of assumptions (which are commonly decided by the modelers), increasing the data requirements for this methodology.

Limitations: Implementing multiple representative households in a CGE model results in increased computational demand and higher running times to solve. Therefore, one needs to consider this limitation when choosing the number of representative groups that fit the computational power available and meet the requirements of the analysis being made.

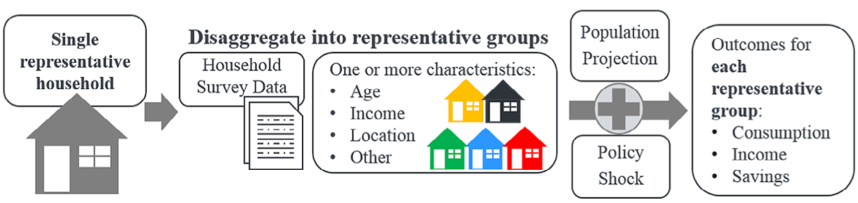

Figure 3. Schematic representation of the approach with multiple households. By the authors.

Another limitation of this method is related to the fact that the income distribution within each representative household is not modeled. By disaggregating the households into groups of equal size and ordering them according to income levels, e.g., in quintiles, the income level of each new representative household is the average of all the households in this group ("representative household"). However, the average income level can still present substantial deviations from the extremes, especially when considering the poorest and richest income groups. Therefore, the method is not well-suited to explore the impacts of climate policies on the poorest 1% of households.

4.2.3. Final Remarks

The methods to analyze the distributional impacts of climate policies using CGE models have varying data requirements and may produce diverging results, as they consider the interactions between household types and the rest of the economy in different ways. GCE models that integrate multiple households in their structural formulations produce detailed output for heterogeneous households while fully considering the interactions and general equilibrium effects between the household types and the economy. On the other hand, micro-simulations can provide detailed outcomes for a large number of household types but do not cover interactions among households. Direct modeling of the income distribution can be implemented with limited data available but does not deal with structural changes or any interactions between households and/or with the economy. The assessment of long-term distributional implications of climate policies requires capturing the heterogeneity in capital endowment and accumulation as well as differences between household types in consumption patterns and responses to price changes. To capture these effects consistently, methodological developments are required beyond the current applications of these methods in (mainly) static models.

The inclusion of multiple household types in CGE models would enable producing scenarios to explore the impacts of climate policies on household income and consumption, considering the interactions among households and between households and the economy. The micro-simulation methods can provide similar information as increasing the number of household types within the CGE model, but potentially for a larger number of household types with fewer computational limitations. The arithmetic micro-simulations enable developing comprehensive income distribution scenarios and account for the full impacts of climate policy on different household types. Behavioral microsimulation methods add to this as they account for changes in the labor force decisions of households which are important for long-term climate policy analysis.

4.2.4. Distributional Impacts in IOMs

Leontief first presented the IOM in 1936 when he created a table representing the economy of the United States in 1919, which depicted the mutual interrelations among industries in that country.[60] IOMs rely on tables that describe sale and purchase relationships between producers and consumers, where rows represent supply and columns the demand.[61] As these tables are fairly accurate in their depiction of inter-industrial relationships, they have been used extensively by economists, environmentalists, and policy makers.[62] On the other hand, IOMs also present limitations due to their simplistic nature, most notably the assumption of fixed coefficients of productions which ignores the possibility of factor substitution.

The disaggregation of households in IOMs for the analysis of distributional impacts is rather straightforward and consists of using household expenditure survey to disaggregate the final consumption into the desired representative groups, often requiring matrix balancing techniques to ensure harmonization between the input–output table and the survey.[63,64] However, as observed by researchers in the 1960s, it is necessary to consider households as heterogeneous entities who have distinct consumption patterns.[65] To address this issue, Miyazawa[66] developed an extension to the IOM by introducing an inter-relational multiplier which computes how direct changes in income of one group results in indirect and induced income changes in another.[67]

Recent applications of IOMs go beyond the monetary framework and include physical units to better portray the energy and environmental systems. Zhang et al.[64] use an IOM with hybrid units and different income groups to investigate the effects of a CO_2 tax on the Chinese economy and the results indicate that while this instrument is successful on reducing emissions with little impact to GDP, the effect on households is regressive and the most affected group are low-income rural households. Ramos Carvajal et al.[67] also uses the Miyazawa model to analyze the expansion of renewable distributed generation of electricity in Spain and suggests that increasing wind and solar electricity generation has the potential to decrease electricity prices and generate a positive impact on households' income.

4.3. Distributional Impacts on Environmental Impact Assessment Models

In contrast to macroeconomic and energy system models, environmental impact assessment models do not necessarily deal with direct distributional impacts in the form of financial implications but focus on estimating the distribution of the environmental burden associated with specific policies. There has been a lengthy discourse in the literature regarding if and how environmental burdens relate to socio-economic status, thus affecting inequalities, especially in the case of air pollution and its impacts on human health.[8,68–70] Results regarding the direction and significance of such a relationship are, however, mixed. Hence, distributional impacts of energy and climate policies reducing the environmental burden may depend on the geographic scope, chosen socio-economic characteristics, and considered environmental risks.[5,8,69–71] This ambivalence is also reflected in the variety of applicable models. The following provides examples of available modeling frameworks and discusses their advantages and limitations.

4.3.1. Methodologies to Assess Environmental Impacts of Policies and Their Distributional Implications

As air pollution directly relates to the energy sector and constitutes the biggest environmental hazard for human health,[9] most impact assessments of energy policies tend to focus on air pollution as their main environmental indicator. Most modeling frameworks in this field follow the Impact Pathway Approach, which links the release of emissions through exposure assessment to predefined impact categories.[20] As air pollution varies locally with meteorological and geographical conditions, spatial analysis and disaggregation offers itself to study distributional impacts. It is also possible to study distributional impacts between representative population groups. By introducing ABM, behavioral reactions to climate and energy policies may also be considered (e.g., a shift in transportation modes). These three concepts—spatial disaggregation, representative population groups, and ABMs—are shortly introduced and discussed in the following.

Spatial Disaggregation: As environmental impact assessment models are primarily designed to simulate and estimate changes in the spatial distribution of the environmental burden, distributional impacts on a spatial scale are often considered implicitly. The IPCC impact assessment,[60] for example, discusses in detail how different countries may be affected by climate change, based on the spatial variation in temperature and meteorological conditions.[72] They conclude that the most vulnerable countries would suffer the most and thus profit the most from climate change mitigation. Such environmental benefits may even offset additional costs.[73,74]

Kitous et al.[73] analyze possible co-benefits from reduced air pollution due to increased climate mitigation on a global level. Although changes in concentration levels are modeled with a spatial resolution of $1^\circ \times 1^\circ$, the analysis concentrates on the country level. Countries such as China and India seem to profit most from additional climate change mitigation efforts, indicating that there are distributional impacts on the country level. Similar results are also provided by Vandyck and Van Regemorter,[74] who applied the same modeling framework.

The same methodological setup is applied as part of the policy impact assessment of the European long-term strategy "A clean planet for all".[75] This study applies the GAINS model,[76–78] which is developed to assess compliance with air pollution control legislation and models air pollution down to street level. Although this modeling framework allows studying distributional impacts between countries, or cities, the policy impact assessment focuses only on the EU level, ignoring any possible effects between or within European countries.

SHERPA is another modeling framework suitable for policy assessment, which is specifically designed to analyze the impacts of different emission sources, i.e., sectors and neighboring regions, on air pollution levels in cities and/or administrative areas.[79–81] With its spatial variability, it provides a flexible and easy-to-apply tool for policy-makers to study the distributional impacts of air pollution mitigation policies between different administrative areas. Spatial variance in the environmental burden within a city can, however, not be analyzed as also acknowledged by Pisoni et al.[82] For this purpose, dedicated city models, such as DIDEM, are required.[83] DIDEM has been specifically developed to study the impact of extending the district heating network in Torino. Although total emission may even rise, the city benefits from improved air quality and reduced associated impacts by relocating emissions from the city center to a rural area.[84] This example shows the relevance of spatial distribution of both emissions and population when it comes to environmental impacts. Although the people in the city center benefit from better air quality, people living next to the new district heating plant may be affected negatively; yet due to the higher population density in the city center, this is still considered a beneficial policy as indicated by a cost–benefit analysis.

The spatial distribution of the environmental burden does, however, not provide any information on the type of distributional impact, i.e., whether a policy has regressive or progressive impacts. For this, we also need to correlate exposure to some socio-economic indicators.

Representative Population Groups: One way to link environmental burden to socio-economic indicators is to define representative population groups and estimate their exposure to environmental risks in different microenvironments based on time–activity patterns.[85–88] Li et al.[86,87] showed that lifelong exposure to different environmental hazards varies significantly between population subgroups differentiated by age, gender, employment level and degree of urbanization, with characteristic behavioral patterns, such as smoking habits and time spent indoors. People living in areas with higher population density, for example, are usually exposed to higher ambient background concentrations. There is also evidence that low-income households show higher exposure to environmental hazards as they spend more time indoors, have usually smaller average room sizes and tend to smoke more often.[89] Gens et al.[85] used a similar model setup to study possible distributional impacts of improved insulation of buildings, which is supposed to reduce ambient air pollution through reduced energy consumption but may affect indoor air quality negatively due to a tighter building envelope. Though a tighter envelope also means less penetration of outdoor air, if significant indoor sources, such as fireplaces, cooking or smoking are present, their increased concentration levels due to lower air-exchange rates may outweigh any benefits related to ambient air quality. Due to the time spent indoors and associated activities, insulation measures may thus have negative impacts on low-income households.[90]

Estimating exposure for representative population subgroups allows to include distributional impacts within countries or administrative regions in environmental impact assessments. Results may, however, differ, depending on how the subgroups are determined, i.e., which socio-economic characteristics are considered. As discussed in Li et al.,[87] different environmental hazards may correlate with different socio-economic characteristics. Population subgroups are usually determined based on micro-census data; its availability determines, in the end, the spatial resolution of the analysis. Also, this data often only contains information about the location of residency, but not about where people work. For simplicity, it is often assumed that ambient concentration levels at the working place are the same as at the residency, ignoring possible distributional effects resulting from moving between different locations. One possible improvement could be to include data from GPS tracking.[91] Combining time–activity patterns with GPS location could allow to estimate individual exposure based on ambient environmental data with a high spatial resolution. The socio-economic characteristics of subgroups have to be matched to time–activity patterns, which are usually based on time use surveys. These surveys provide static diaries with additional socio-economic information.

To avoid biased results, the models are usually run in a Monte Carlo simulation to capture uncertainty, iterating through different possible diaries, resulting in an exposure distribution for each subgroup. As these diaries are, however, exogenously determined, the models are not able to capture any behavioral reactions. With improved building insulation, for example, people may open windows more frequently as they notice a decline in indoor air quality. Similarly, better access to public transport and cycling lanes will affect the decision to travel by private cars. To also capture these responses and their impact on the environmental burden, especially in cities, agent-based exposure models were recently developed.

Agent-Based Models: As described in Vallamsundar et al., Chapizanis et al., and Yang et al.,[92–94] ABM is used to estimate the dynamic exposure of population subgroups or individual agents to environmental hazards by combining, for example, air pollution maps with street and building information and an ABM layer. The ABM simulates the movement (behavior) of different agents according to their socio-economic characteristics and associated behavioral rules. Agents then react dynamically to changed situations, e.g., closed roads or improved public transport. With this approach, it is possible to also account for spatial variations in exposure and their distributional impacts within administrative areas. The modeled agents depend on the available information and data regarding time–activity patterns, socio-economic status, movement profiles, and considered microenvironments. In addition, decision-making rules may differ in each microenvironment or from region to region. Due to high data requirements, ABMs are usually only applicable to smaller domains, such as individual cities. Their current application seems to also focus on policy implications in the transport sector due to its dominance in urban air pollution. By considering dynamic exposure of different population subgroups, ABM frameworks may help policymakers to identify vulnerable subgroups and design better, targeted mitigation policies, effectively reducing distributional impacts. Despite their potential and flexibility, their suitability for policy analysis could be limited due to their complexity and missing knowledge on how socio-economic status affects mobility or consumption patterns in different regions or administrative areas.

4.3.2. Data, Metrics, and Limitations

Environmental impact assessment models require a lot of data. This data dependency increases the more detailed distributional impacts are to be studied. To differentiate population subgroups, spatially resolved population data has to be combined with socio-economic characteristics, e.g., from micro-census data, often only available on a coarser resolution (census or administrative level) due to data protection issues. In addition to having to fuse different spatial scales and match different socio-economic differentiation, policy assessment is usually done prospectively and thus requires projections for future years. Available population projections consider changes in age distribution due to changing life expectancy and birth rates and partly also spatial changes due to increased urbanization. It is, however, not possible to project the distribution of socio-economic characteristics without introducing a substantial amount of new uncertainties. Though changes in socio-economic characteristics such as employment and income level may, for example, be determined by sequential analysis,[86,87] high uncertainties and increased complexity may result in difficulties to interpret the policy assessment results.

Improved exposure assessment considering different microenvironments additionally requires information about time–activity patterns. These are usually derived based on diaries, constituting only a snapshot in time of typical activities, which may also change in the future, also as a response to policies. Without modeling this change in activities, e.g., with ABMs, or considering such implications in the scenario setup, these behavioral responses are neglected in the analysis. Relevant information linking socio-economic characteristics to activity/movement patterns and to derive corresponding decision rules could be collected from wearable sensors[95] or by coupling with other models, e.g., energy system models, transport models, or economic models with a suitable disaggregation, especially with regard to households.

4.3.3. Final Remarks

Environmental impacts are often modeled with a high spatial resolution that would allow studying distributional impacts on a spatial level, e.g., between neighborhoods, but the analysis is often carried out only on a more aggregated, administrative level. Thus, most policy assessments focus on differences between countries, ignoring potential distributional impacts within countries due to changes in the environmental burden. Available frameworks to analyze these distributional impacts on population-level are characterized by high uncertainty and depend on available data quality. Static approaches based on simulating exposure in different microenvironments according to time–activity patterns can only provide a snapshot of possible distributional impacts. Assumptions about changing activities in the future need to be explicitly included in the scenario setup. ABMs offer the possibility to also consider behavioral feedbacks, i.e., changes in activities, but only as long as decision rules are known. In addition, ABMs are potentially limited in their spatial domain due to increased data requirements. Finally, all discussed frameworks do not consider any financial implications of reduced environmental burden. Although health impacts are sometimes expressed as external costs, their financial implications with regard to distributional impacts are often not discussed. As mentioned in ref. [8], not all environmental impacts can be expressed in market-relevant terms. If they are, however, it is possible to also feed their implications back to economic models. Less work-loss days resulting from improved air pollution, for example, could increase labor availability in CGE models.[75] Including air pollution costs in energy system models may affect the energy transition pathways,[96] and thus have direct distributional impacts. By coupling environmental impact models with economic models would allow studying both the environmental and financial dimensions of distributional impacts or energy or climate policies.

5. Integrated Solutions

The previous sections have shown how distributional impacts of energy and environmental policies can be integrated into energy system models, macroeconomic models, and environmental models. However, due to the unique formulation of each modeling framework, it is a challenge to develop a comprehensive method that includes the energy, socio-economic, and environmental dimensions altogether. An integrated solution attempts to link two or more models in a common framework to close the gap between different perspectives and mitigate the weaknesses of individual modeling techniques.

Although the process of linking two or more of the aforementioned models is not new and is further reviewed by Korkmaz et al.,[97] cases applied to the investigation of distributional effects among households are still scarce. For this reason, we focus this section on two existing strategies: 1) linking macroeconomic and micro-simulation models, and 2) linking partial equilibrium models with other models.

5.1. Linking Macroeconomic and Micro-Simulation Models

Micro-simulation models may include a very large number of household types, even considering all households from a sample survey as separate household types. These models can vary widely in sophistication and granularity, ranging from simple accounting/arithmetic methods to approaches that include behavioral responses of households to changes in labor markets and product prices (i.e., changes in savings behavior). The micro-simulation and the macroeconomic models can operate in a sequential (top-down) form or in an iterative format (top-down/bottom-up), in which there is a feedback loop between the models,[30] as shown in **Figure 4**.

5.1.1. Sequential Approach

In sequential studies, changes in labor and capital markets and consumption are first determined in the CGE model and are then integrated into the Micro-Simulation model as exogenous variables, which is then used to determine the impacts on households.[98] These are based on a set of equations quantifying income, expenditures, taxes, and savings for different household types constrained by the survey data and CGE model results. These models usually include a detailed representation of taxes and transfers, and determine income of different household types.[99] Commonly, several output variables of CGE models are used as inputs to Micro-Simulation models, which can disaggregate the results over multiple household types, including wages, prices of goods, consumption, the sectoral composition of labor, etc.[100]

In addition, some modeling approaches include behavioral equations, which determine the behavior of households (e.g., occupational choices) based on characteristics of individuals from the household survey.[101] This approach can capture changes in population structure and employment shifts among sectors using appropriate weighting. These models estimate econometrically the probability for household members to be in a certain labor market, derived from implicit utility functions and do not identify a particular labor market choice for each individual, but generate a probability distribution over the labor market choices of the population.[101] Some constraints have to be imposed to maintain consistency between the CGE and the micro-simulation models with respect to total employment, wage rates, and income levels.[99] This is usually done by adjusting the parameterization of the CGE model aiming to minimize the differences between the model results, while alternative approaches have been also analyzed.[99]

Although most applications of this approach are performed with static CGE models, attempts exist to use dynamic CGE models. Buddelmeyer et al.[102] combine a dynamic CGE model for Australia with a Micro-Simulation model, with both models using a similar population structure. The CGE model results are downscaled to the level of households (through Micro-Simulation modeling) and reweighted for structural changes in the population. The GTAP poverty framework (GTAP-Pov) is a micro-simulation model drawing on national household survey data, sequentially linked to a “standard” GTAP CGE model,[103,104] used to perform policy analysis for single countries.

Data requirements include information on taxes, social benefits, hours worked, as well as information on the benefits system to determine implications of changes in a household earning for tax payments and/or eligibility for benefits. Behavioral micro-simulation is more data-intensive as it needs background data that characterize household members to define behavioral choice modeling. To model occupational choices of households, information on household characteristics is required, e.g., age, gender, education, skills, children under six, etc.

In modeling approaches not including behavioral aspects, the changes in economic variables (i.e., employment, consumption) are determined by the survey data and the aggregate changes in the representative households (modeled with CGE). Therefore, this method cannot capture the characteristics of the individual households.[102] However, the inclusion of behavioral aspects may overcome these limitations and help the analysis of household economic behavior such as consumption preferences.

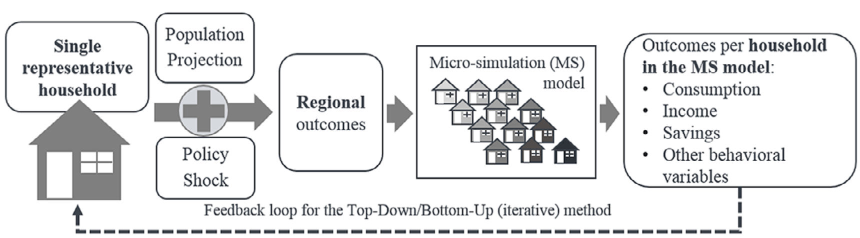

Figure 4. Schematic representation of the approach with micro-simulation. By the authors.

5.1.2. Iterative Approach

The iterative approach ensures that the information from micro-simulation models is fed back to the CGE or energy system models aiming to converge to a common solution in a few iterative steps. In the case of CGEs, the variables iterated across models are changes in employment, labor supply, wages, consumption patterns, and prices.[98] In ref. [105], the CGE determines and passes the prices, household income, goods supply and labor demand on to the micro-simulation model, which in turn calculates endogenously household incomes, consumption, labor supply, and unemployment. Labor supply and consumption patterns change in both models as households respond to changes in wage rates, with the loop continuing until the models converge on consumption and labor supply.

Böhringer et al.[106] coupled a CGE model with a micro-simulation model to assess the impacts of a green tax reform where additional revenues are redistributed lump-sum to Spanish households on an equal-per-capita basis. The quantitative evidence from coupled CGE and micro-simulation analyses showed that such a green tax reform leads to a substantial reduction in harmful emissions while having a progressive impact on low-income households.

The way of modeling feedback from the micro-simulation to the CGE or energy system model influences the results of the approach. Results can also be affected by observed inconsistencies between the data from household surveys and the SAM used in CGE modeling or energy demand disaggregation in the energy system model. This can be prevented by adjusting either the micro or the macro data, at the stage of model development.

Rutherford et al.[107] showed that under some conditions (i.e., households not changing occupation), the iterative micro-simulation method resembles the same results as a multiple households CGE model. The combined CGE–MicroSimulation approach has the advantage of numerical tractability and reduced running time with respect to large numbers of households in income–expenditure surveys.[106]

5.1.3. Hybrid Approach

Hybrid approaches have also been developed, the most common of which is the combination of a multiple household CGE (representing a small number of household types) with direct modeling of the income distribution and micro-simulation to produce results for a larger number of household types. This approach captures the general equilibrium effects (related to changes in prices, demand) between a large number of household categories within the CGE modeling framework.[74,108,109]

The hybrid approaches are even more data-intensive as they require (in addition to full-scale SAM) surveys with household-level data on 1) expenditures on goods, 2) wages and capital income, 3) assets and demographic projection on changes in household characteristics, but also household-level information on taxes paid, social benefits, and labor.

5.2. Integrated Solutions with Partial Equilibrium

Partial equilibrium models are well-equipped as part of a suite of integrated solutions to assess the distributional impacts of energy and climate policies. The focus of partial equilibrium models is on the techno-economic pathways, which can include linking to other models or applying the equity evaluation.

As described in Section 4.1 and shown in Table 1, there are three variations to link models: coupling, soft-linking, and hard-linking—each with its own advantages and disadvantages. The advantage of model linking methods is to retain a high level of detail in each of the separate models—similarly to disaggregation—and at the same time to maintain the flexibility of the different modeling frameworks. Retaining the positive aspects of the partial equilibrium framework to assess the long-term implications for energy transitions requires preserving the main method such that the soft-linking approach is most common. Capros et al.[110] applied the PRIMES model to quantify the impacts of the European "Clean Energy for all Europeans" package. The PRIMES model links a suite of detailed sector models, which although did not specifically aim to address distributional impacts, identifies specific challenges that not only impact the policy objectives but also will have effects to consumers in terms of benefits and economic repercussions.

Fell et al.[15] reviewed integrated ways to capture the distributional impacts of long-term transitions by linking a partial equilibrium model with a higher level of disaggregation in the household sector with a model specifically designed to evaluate distributional impacts. This mixed-methods approach, however, allows to identify potential areas in long-term policies that might be of concern with regard to distributional impacts. Pye et al.[34] apply an equity evaluation as a means of linking information from different sources and models without changing the structure of each method.

The linked model approach of partial equilibrium with other models, such as macroeconomic models, is a powerful tool that offers a unique insight through the combination of long-term energy and climate policy pathways in conjunction with a view on their potential distributional impacts on specific groups. Soft-linking allows each model to maintain its framework and strengths without the burden of increasing the computational time or the model complexity.

6. Conclusion and Outlook

In this work, we reviewed several modeling frameworks that are 1) commonly utilized for energy and environmental policy analysis and 2) capable of assessing the distributional impacts of such policies. This study comes from the necessity to better contemplate the distributional aspects of measures that aim at decreasing GHG emissions. This need is clearly stated at the 2030 Agenda for Sustainable Development signed by the United Nations Member States and is reflected on protests against fiscal policies that, despite aimed at curbing emissions, end up impacting low-income earners as it happened in Yellow vest movement.

Distributional effects refer to how the gains and costs of a project or policy are distributed among its participants, which in terms of policy-making may refer to different regions, sectors, and households. This work focuses on the last dimension and examples of distributional effects, in this case, are the incidence of taxes, income growth, energy consumption, and health damages caused by environmentally harming activities.

A number of modeling frameworks capable of depicting distributional impacts in different dimensions is presented, ranging from earlier methods such as energy and IOMs to more recent environmental impact assessment tools. The fundamentals of each framework are briefly described to provide a complete view of the diversity of modeling tools available for energy and environmental policy analysis.

Following, in Section 4, we discussed three individual modeling techniques with distinct focusses and how they incorporate distributional impacts into their analyses. First, energy system models using partial equilibrium formulation can be used to assess the technological requirements and costs of energy and environmental policies due to their high level of technical detail. However, the lack of feedback with other economic sectors constrains their use in climate policy analysis. Next, we move to general equilibrium models which are capable of accounting for feedback effects between sectors and regions in exchange for a less detailed technical description of the energy system. Finally, environmental impacts assessment models make it possible to estimate the health impacts of air pollution from fossil-fuel consumption for energy-related activities.

Integrated solutions that involve linking two or more models in a single unified framework are reviewed in Section 5. We mainly discuss the combination of macroeconomic with micro-simulation models and integrated solutions involving partial equilibrium models because these are widely used to better represent distributional effects.

Among the techniques discussed in Section 4 and 5, it is clear that a common solution for the inclusion of distributional effects on modeling frameworks is the disaggregation of sectors or households. The main challenge of this approach is the availability of data because it requires describing each individual representative household with specific information depending on the modeling framework being used. Therefore, the scarcity of data and difficult access to household surveys are obstacles that should be tackled to improve the analyses of distributional impacts of energy and environmental policies, especially those conducted by governments, which should in theory have easier access to these resources.

Integrated solutions offer a pathway to reconcile the strengths of different modeling approaches, but literature is scarce on linking different model types in a unified framework and also consider different household groups. In such a modeling exercise, data requirements are very high and there is also the issue of how the different models communicate with each other. In this case, one viable option is to select one central model that receives input from the others and reacts accordingly, such as the PRIMES or PROMETHEUS model,[14,111] with the addition of multiple representative households from Section 4.2 or an integrated micro-simulation.[112] Also, starting with static analysis of a single region would help obtain useful insights for expanding the framework in future exercises.

Supporting Information

Supporting Information is available from the Wiley Online Library or from the author.

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Conflict of Interest

The authors declare no conflict of interest.

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