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Methods for including income distribution in global CGE models for long-term climate change research

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ABSTRACT

The consequences of climate policy and the impacts of climate change vary among different types of households depending on their income level, expenditure pattern, and other socioeconomic characteristics. Global economy-environment models that are used to assess climate change issues traditionally do not distinguish households by income or other attributes. To facilitate progress in this area, we review and assess literature on methods to include household heterogeneity in global long-term Computable General Equilibrium (CGE) models. We distinguish among three categories of approaches: 1) the explicit modeling of multiple household types within the CGE framework, 2) micro-simulation modeling, and 3) direct modeling of income distribution. For each of these approaches we describe the method, key assumptions, limitations and several prominent examples from the literature. Moreover, we discuss data needs, including the contents of household survey data, their availability and processing. We conclude with an overview of what each method could provide for global, long-term climate-related research.

1. Introduction

The success of climate change policies is not only about how much climate damages they avoid and how much they impact the whole economy but also on how costs and benefits of climate change mitigation actions are distributed among households. Indeed both the consequences of climate policy and the impacts of climate change vary between different types of households, and then winners and losers should be clearly identified in order to compensate the latter and make the policy acceptable. For instance, Hertel et al. (2010) found considerable differences between household groups for the poverty effects of crop yield changes due to climate change, driven mostly by differences in earnings and ownership structure of agricultural households. Rausch et al. (2011) found that welfare implications of a carbon tax vary between households at different income- and education levels and across ethnic groups in the United States, due to differences in occupation, and income and expenditure patterns. Hallegatte et al. (2014) recently developed a framework that identifies the channels through which households may escape or fall into poverty and how these channels relate to climate change: prices, assets, productivity and opportunities. Climate impacts and greenhouse gas (GHG) mitigation impacts each of these channels differently, and all of these channels are macro-economically linked. Global long-term general equilibrium models are useful tools to consistently analyse future developments of these channels at the global level and consistently link the macro-economic implications from changes in prices, assets, productivity and opportunities. However, analyzing the implications of climate change for poverty and income distribution requires that such models explicitly represent different household groups.

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Although country level applications of CGE models often include some degree of heterogeneous households, global economy-environment models that are used to assess climate change issues typically do not distinguish household groups by income or other attributes. Recently, a few partial equilibrium models that focus on the energy system and greenhouse gas emission mitigation have introduced sub-regional distributions of households (for an overview see Krey, 2014). Some of these studies defined a small set of household types according to a combination of income and urban-rural status (Ekholm et al., 2010; van Ruijven et al., 2011). These models were used to analyze the implications of future changes in urbanization (Krey et al., 2012), income distribution (van Ruijven et al., 2011) or access to energy for energy use and emissions (Pachauri et al., 2013) and whether consequences of mitigation policies differ across household types (Daioglou et al., 2012). Other studies used a global general equilibrium model, and characterized a representative household on the basis of underlying changes in age, household size, or urban-rural status, to analyze the effect of demographic change on economic growth, energy use and emissions (Dalton et al., 2008; Melnikov et al., 2012; O'Neill et al., 2010). Some studies have used global general equilibrium models to analyze the impacts of climate change on different household groups by extending the number household types for several countries (Bouet et al., 2013) or by performing a sequential microsimulation for a number of countries (Ahmed et al., 2011; Hertel et al., 2010). Another part of the literature applied non-CGE tools to analyze national level impacts of GHG mitigation policies (Blonz et al., 2010; Büchs et al., 2011; Jorgenson et al., 2011; Parry and Williams, 2010; Rao, 2013).

So far, analyses of long-term impacts of climate change seldom include changes in income distribution (van Ruijven et al., 2014), though this might change in the near future as the new scenarios framework provides new handles for including this aspect of socioeconomic vulnerability. As part of the process to develop new scenarios for global climate change research (Kriegler et al., 2012; Moss et al., 2010; van Vuuren et al., 2012) an effort is underway to enrich the recently developed Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014; O'Neill et al., in press) with projections of changes in income distribution. On top of projections of demographic change (KC. and Lutz, in press), urbanization (Jiang and O'Neill, in press) and GDP (Dellink et al., in press; Crespo Cuaresma, in press; Leimbach et al., in press). Several existing methods, such as those described by Bussolo et al. (2010); Hughes et al. (2009); Kemp-Benedict (2011) and Van der Mensbrugghe (2015) are being applied to develop poverty and income distribution projection that are consistent with the SSPs.

To facilitate progress in the modeling of household heterogeneity within the context of long-term global studies, this paper provides an overview of the different methods that exist for general equilibrium models to include income distribution. Most of these methods have been developed in the context of development economics and within this field several overviews exist (Ahmed and O' Donoghue, 2007; Bourguignon and Bussolo, 2013; Savard, 2003). However, most applications of these methods in the literature use static CGE models and analyze short-term poverty impacts of development-related policy shocks. Hence, these models do not have to account for several factors that are relevant for long-term projections and climate change issues, such as changes in population structure (age, urbanization, education). In this paper, we will expand on the existing reviews by adding examples that focus on the longer-term and on climate-related applications. We will describe a range of methods available with particular emphasis on their suitability for use with global long-term Computable General Equilibrium (CGE) frameworks.

In this paper, Section 2 introduces different aspects of household heterogeneity in CGE models and the existing approaches to analyze this. Section 3 discusses the explicit modeling of multi-household CGE models, Section 4 describes micro-simulation approaches and Section 5 focuses on direct modeling of income distribution. For each of these approaches we present a description of the basic method, the key assumptions and limitations and several prominent examples from the literature. Section 6 describes the combination of these methodologies in hybrid approaches. Section 7 discusses data availability and processing and Section 8 discusses and concludes this paper.

2. Approaches to modeling income distribution within CGE frameworks

In many global CGE models, all households within a country or other model region are aggregated into a single representative household (Fig. 2). This representative household is endowed with labor and

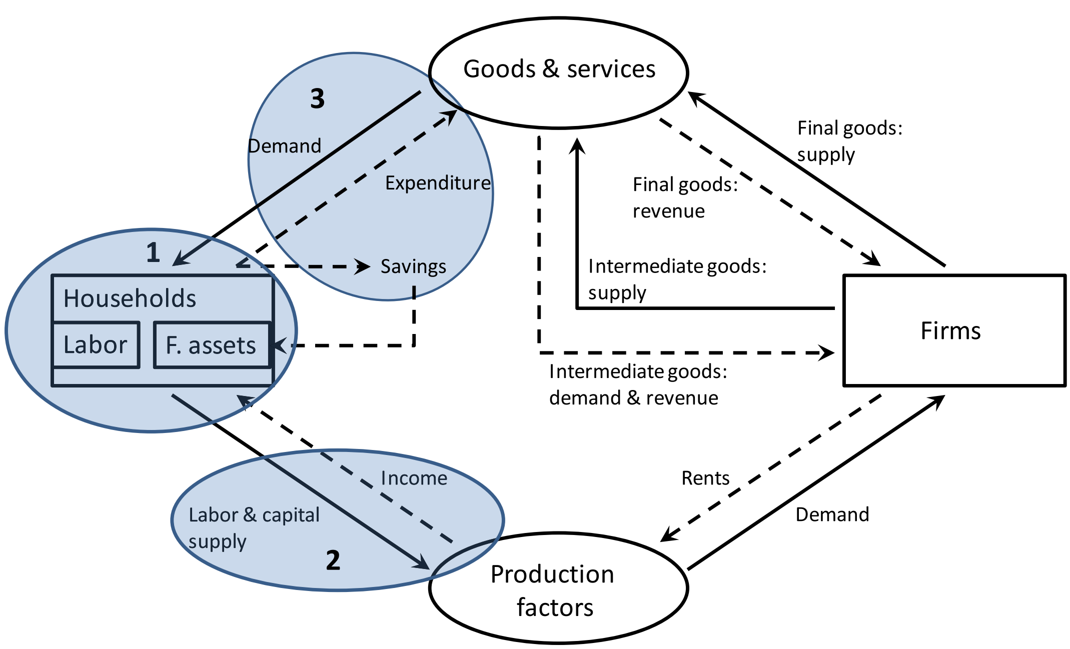

Fig. 1. Schematic representation of the flows (white circles and arrows) in a basic CGE model between the stocks of firms and households (rectangles). Households provide production factors (labor and capital) to firms and firms provide goods and services to each other and to households. The dashed arrows indicate monetary flows (income, expenditure, revenue, rents); the solid arrows indicate flows of products/factors in the opposite direction. Shaded circles indicate the three different aspects of household heterogeneity in CGE models indicated by Bertola et al. (2006).

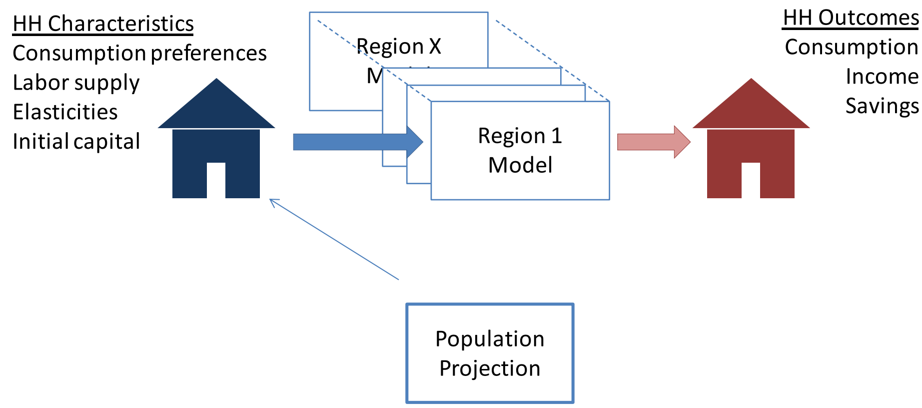

Fig. 2. Schematic representation of a CGE model with a single representative household.

financial assets (and natural resources) and the consumption preferences are parameterized to simulate the aggregated behavior of all households with respect to consumption patterns and savings. In this paper, we will use the representative household approach as benchmark for comparison of all other methods. The role of households in general equilibrium models includes several aspects (Fig. 1). Households receive income in return for their supply of production factors (labor, capital, and in some cases land) to firms. Households receive (buy) goods from firms in return for their expenditures. Two main dynamics increase income of households over time: first, increased labor productivity enables firms to produce more goods per unit of labor, which leads to higher labor income per hour worked. Second, the savings behavior determines how much capital households build up, which leads to more capital that can be supplied to firms to generate capital income.

Heterogeneity across household types can be modeled for three aspects of households in CGE models (indicated with the numbered circles in Fig. 1) (Bertola et al., 2006). The first aspect (1 in Fig. 1) is heterogeneity in factor endowments, such as differences in financial assets or labor supply across households (e.g. education, number of working household members). If one only includes this aspect in an analysis, the implicit assumption is that markets for capital and labor are perfect, since all household groups receive the same returns to capital and labor. The second aspect (2 in Fig. 1) covers heterogeneity in wage rates (e.g. multiple labor markets) and/or different return rates to capital for different households (e.g. imperfect capital markets like credit rationing according to income), but also household decisions on what share of the labor endowment participates on the labor market depending on the household characteristics (age, children, leisure, health). The third aspect (3 in Fig. 1) deals with heterogeneity in preferences and savings. This can be achieved through different means, either by directly specifying differences in consumption budgets across households, or indirectly by differentiating parameters in utility functions such as preference shares and/or substitution elasticities across household types. Similarly, households can make different decisions on saving vs consuming.

Several approaches exist to include income distribution in CGE models and several categorizations have been published before (Ahmed and O' Donoghue, 2007; Bourguignon and Bussolo, 2013; Savard, 2003). The main categories that these typologies distinguish are 1) explicit representation of multiple household types, 2) coupling macro-level models with micro-simulation models and 3) direct modeling of income distributions derived from historic data. In the first approach, the number of household types within the general equilibrium model is increased to several types, or even all individual households from a survey. Each household type has a separate utility function and its decisions are modeled integrally within the CGE model. Household types generally differ in terms of labor types (urban/rural, skilled/unskilled, formal/informal, wage/self-employed) and consumption patterns (either only for the base year and/or for changing consumption preferences over time) based on household level data on all these aspects (Davies, 2009). The second approach, micro-simulation, employs a separate household-level model, informed by survey data and aggregate outcomes from the CGE model, to simulate the impacts on multiple household types (ranging from several types to thousands of individual households) of macro-changes in employment, wages, capital returns, and prices. These models can take an accounting approach that allocates aggregate economic outcomes across household types according to fixed rules, or they can include behavioral responses that simulate households' occupational decisions as result of macro-economic shocks. Micro-simulation models can be used for post-CGE calculations ('sequential'), or be applied in iteration with CGE's to converge to a - common solution. Finally, direct modeling of income distribution focuses on income only, ignoring differences between households in terms of expenditures or income-sources. It assumes or estimates from household-level income data a distribution function of income, which in most studies is kept constant in future projections.

Each of these approaches can be related to the aspects of household heterogeneity that Bertola et al. (2006) distinguished. In multi-household CGE models and in microsimulation models, all the aspects of household heterogeneity can be included. However, this is not necessarily done in all studies. Since many papers analyze poverty and use static CGE models, they focus on the labor supply and labor income aspects while often ignoring heterogeneity in capital[i] (endowment, savings, supply, income) and aggregating heterogeneity in consumption into a household-type-specific consumer price index. Direct modeling of (income) distribution could be applied to all three aspects of household heterogeneity as well, although that would lead to consistency issues between the different distributions that would be used. However, in general, most studies that use this approach derive a distribution for labor income or total income and don't specify heterogeneity in consumption.

3. Multiple households in the CGE model

3.1. Description of the method

In this approach the number of households is extended from a single representative household to multiple representative household types (Fig. 3). Except for increasing the number of households, the structure of the CGE model remains the same. Labor supply, consumption preferences, and substitution elasticities are specified separately for each household type. Outcomes for savings, consumption and income are generated for each household type, and general equilibrium effects

[i] It is worthwhile noting here that survey data on capital income are notoriously weak, especially for developing countries.

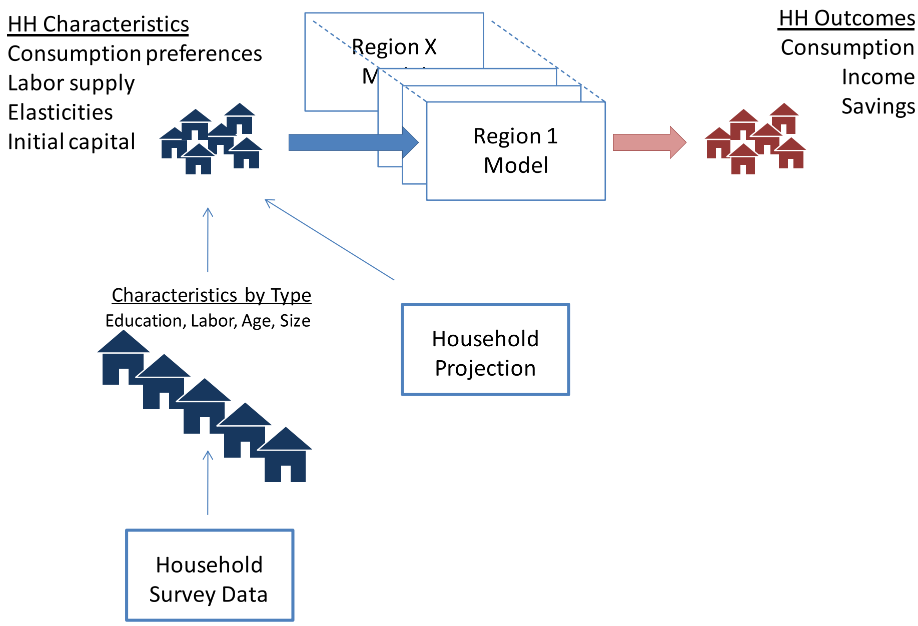

Fig. 3. Schematic representation of a CGE model with multiple household types.

(interactions among household types through prices) are captured. An income distribution for each model region can be produced, consisting of the income of each household type. For this method, "multiple households" can refer to either just a few households or all households in a nationally representative household survey (thousands). The choice of the number of households depends on computational, data or application-specific considerations.

3.2. Key assumptions and limitations

A key assumption related to this method is the definition of household types. This is especially relevant when one does not use thousands of households from a survey directly, but aggregates them into a small number of household types. In the context of long-term models, running forward for 30 to 100 years, the definition of household types must be done with care to account for the fact that many characteristics of households change over time. For example, household members age over time, rural households migrate and become urban, household size changes over the life cycle, and education status changes. In static or recursive-dynamic models, the changes in household characteristics can be easily taken into account because households make decisions without foresight and therefore their future characteristics are not relevant to their current decisions. As an example, it is possible to define households based on the age of the household head in such cases. A household type defined as "middle-aged households" will make decisions without having to account for the fact that members of this group will become members of a new household type, e.g. "elderly households," at some point in the future. However, in forward-looking models, household types should not be defined such that households would potentially move from one type to another over time, otherwise the structure becomes logically inconsistent. In the example of household types defined by age, middle-aged households in a forward looking model would be making decisions to maximize the well-being of all middle aged households now and in the future, rather than maximizing their own wellbeing in the future when they become elderly. This problem has been addressed in the case of age by defining household types in terms of cohorts rather than age *per se*, where a cohort tracks a group of a certain age in the base year as it ages over time. The cohort approach is the foundation of the structure of Overlapping Generations (OLG) models and has been extended to models with Infinitely Lived Agents (ILA) by linking current cohorts with cohorts of their descendants to constitute dynasties (Bertola et al., 2006; Dalton et al., 2008).

Another aspect of defining household types for analyzing income distribution is that, if the household types used are not defined by income but by another characteristic (e.g. age, employment, education), the distribution may not represent well the true income distribution. Even if correcting for such mismatch in base year distributions, the change in distribution over time could be different than the changes in the true income distribution due to economic development or policy shocks. A related aspect is that (change in) income distribution depends on the fiscal system as well, which leads to high data requirements and specification of fiscal rules when including this approach in global models.

If occupational choices of households are an important aspect of the study, the multi-household CGE model has limited capacities. According to Colombo (2010) and Savard (2003) household types in CGE models cannot change occupation, contrary to behavioral micro-simulation models (see Section 4.1.2) . Hence, CGE models with large numbers of household types have done a poorer job of capturing occupational (behavioral) responses at the household level than behavioral micro-simulation models. However, theoretically there is no reason for CGE models to exclude this capability.

A practical issue that is relevant for all methods in this paper, but most prominent for the multi-household CGE method is that consumption levels, incomes and assets can deviate substantially between household survey data and national accounts (Deaton, 2001; Deaton and Kozel, 2005). Therefore, one has to reconcile the data from the household survey with the data in the CGE model, which are based on social accounting matrices (SAM). To do this, one can adjust the survey, the SAM or both, but in any case one loses original information (see a detailed discussion on this issue in Section 7.2).

A final limitation of this approach is that the computation time can become large as the number of household types increases. In the case of forward looking models, even a small number of household types increases numerical complexity, making it harder to converge on a solution and in some cases significantly increasing computation time.

3.3. Examples

The literature on multiple household CGE models is dominated by static CGE models and analyses of the distributional impacts of trade

Table 1
Main characteristics of recent papers using multiple household CGE models.

Reference	Household types	Country	CGE type	Focus	Model	Time
Acharya (2011)	4: U, Large R, Small R, Landless R	Nepal	static + RD	trade liberalization		1996-2006
Acharya et al. (2012)	4: U, Large R, Small R, Landless R	Nepal	static	trade liberalization		1996-2006
Agenor et al. (2003)	U/R + skills		static	exogenous shocks	IMMPA	
Annabi et al. (2013)	all from survey	Canada	RD	working income tax		
Bouet et al. (2013)	13 to 39	Global, Brazil, Pakistan, Tanzania, Uruguay and Vietnam	RD	trade liberalization	MIRAGE	2004-2025
Bourguignon et al. (2003)	all from survey	Indonesia	static	trade & exogenous shocks		
Buffie and Atolia (2012)	2: work, capital	Zambia	dynamic	trade liberalization		
Cockburn (2004)	all from survey	Nepal	static	trade liberalization		
Cockburn et al. (2010)	all from survey	Nepal, Philippines	static	trade liberalization		
Durand-Lasserve et al. (2015)	all from survey	Indonesia	RD	Fossil-fuel subsidies reform	ENV-Linkages	2010-2020
Feltenstein and Cyan (2013)	2: U/R	Pakistan	dynamic FL	Sectoral tax potential		2004-2011
Filipski et al. (2011)	6: Ag/non-ag, gender, nationality	Dominican Republic	static	trade liberalization		
Gilbert and Banik (2010)	4 to 19	South East Asia	static	infrastructure investment		
Jonasson et al. (2014)	6	Ghana, Malawi, Bangladesh, Vietnam, Guatamala, Nicaragua		agricultural policies	DEVPEM	
Melnikov et al. (2012)	6: 3 urban and 3 rural dynasties	India	dynamic FL	Comparing multi-HH CGE with representative HH	iPETS	2000-2100
Naranpanawa et al. (2011)	5: U/R estate low inc., U/R high inc.	Sri Lanka	static	trade liberalization		
Naranpanawa and Bandara (2012)	5: U/R estate low inc., U/R high inc.	Sri Lanka	static	fuel prices		
Ojha et al. (2013)	9: R non-ag self-emp, ag lab, lab, ag self-emp,U: self-emp lab, salaried, casual, other	India	RD	economic growth strategies		2004-2030
Rausch et al. (2011)	all from survey	USA	static	carbon pricing	USREP	
Rausch and Mowers (2012)	9: region, income	USA	static	carbon pricing	USREP	
Rutherford et al. (2006)	all from survey	Russia	static	trade liberalization		
Tarr (2012)	all from survey	Russia	static	trade liberalization		
Yusuf and Resosudarmo (2015)	200: U/R income centiles	Indonesia	static	carbon tax	ORANI-G	

Abbreviations: U: Urban, R: Rural, Ag: Agriculture, inc: income, self-emp: self-employed RD: Recursive Dynamic, FL: Forward Looking.

liberalization (see Table 1). However, some studies take a long-term approach, such as Ojha et al. (2013), and others apply multi household CGE models to climate-relevant topics (Naranpanawa and Bandara, 2012; Rausch and Mowers, 2012; Rausch et al., 2011; Yusuf and Resosudarmo, 2015).

Ojha et al. (2013) modeled nine household types within a recursive dynamic CGE framework to analyze the implications of several different economic growth strategies for India. Each household type has an initial endowment of labor at different education levels and capital. A demographic scenario is combined with a baseline scenario for GDP growth as starting point for policy analyses. The study looks into different growth strategies based on expanding human capital (education expenditure), physical capital and technological progress (higher TFP growth) and concludes that only a balanced mix of these strategies leads to reduced inequality.

Rausch et al. (2011) used the USREP model, a static CGE model for the US that includes 15,588 household types as individual agents, to analyze the impacts of a 20 USD/tCO_2 carbon price under three different revenue recycling scenarios. Their most interesting finding in this context is that "variation in impacts within broad socioeconomic groups may swamp the average variation across groups". This highlights the relevance of including household heterogeneity in climate change research.

The version of the MIRAGE model held at the International Food Policy Research Institute (IFPRI) recently expanded from a single representative household to several households within the CGE model for a number of regions (Bouet et al., 2013). MIRAGE is a recursive dynamic CGE model with global coverage. The increase of household types was limited to several countries for which high quality data were available and the number of households differ per country depending on the results of a clustering analysis to generate homogenous household groups: Brazil (13 households), Pakistan (25 households), Tanzania (35 households), Uruguay (39 households) and Vietnam (33 households). The income and consumption functions moved from the representative household to the level of individual household types, but many parameters, such as the substitution elasticity for consumption initially remained the same for all household types. Each household type is assumed to be representative for all households in the group, without taking further diversity into account. It is unclear how demographic changes (such as aging or urbanization) are taken into account in this approach. However, since the model was applied to analyze the consequences of trade liberalization for households in a relatively short term time frame (2025), this might be of less relevance than for long-term global models.

4. Micro-simulation (MS) of a large number of household types

Micro-simulation models simulate outcomes for a large number of household types consistent with outcomes at a higher level of aggregation as determined in the macro model (Fig. 4). In micro-simulation models there may be a very large number of household types, up to and including treating each household in a nationally representative sample survey as its own type. These models differ from multiple household CGE models, as described in Section 3, in that the multiple household CGE models *replace* a single household with multiple households within the macro model itself, whereas a micro-simulation model uses the results of the household type(s) in the macro model to simulate outcomes with a higher degree of heterogeneity. Micro-simulation models also differ from direct modeling of income distribution (see Section 5) in that income distribution is not specified directly in the micro-simulation approach, but rather is an outcome of a differentiation of economic characteristics across a number of specifically defined

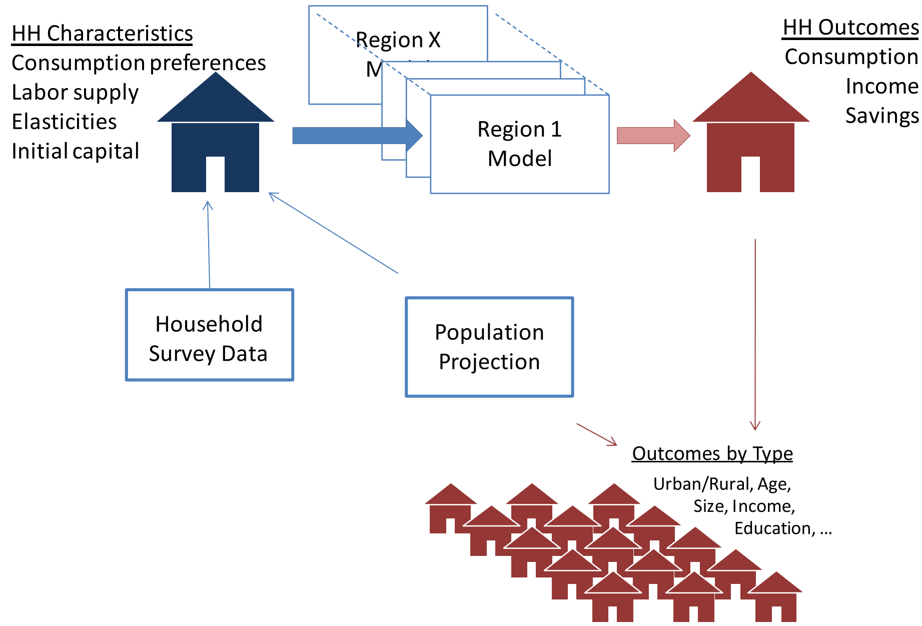

Fig. 4. Schematic representation of micro-simulation.

household types. Micro-simulation models can be used as sequential calculation after the CGE run (top-down) or in iteration between micro-simulation and CGE model (top-down/bottom-up). In addition, micro-simulation models can vary widely in sophistication, from non-behavioral/arithmetic/accounting approaches, to approaches that include behavioral responses (i.e., changes in occupation or savings behavior) of households (or household members) to changes in labor markets and prices of goods. Rutherford et al. (2006) have shown that under some conditions (i.e. arithmetic, households not changing occupation) the iterative micro-simulation method resembles the same results as a multiple households CGE model.

In this section, we will first discuss the sequential approaches, followed by the iterative approach. For the sequential approach we distinguish between arithmetic and behavioral MS models; the iterative approach only uses behavioral micro-simulation models.

Even though MS models present their results at the level of (many) household types, this does not mean that these models also include all relevant dynamics to accurately determine such detailed results. Buddelmeyer et al. (2008) are very open about this in their report on an arithmetic micro-simulation model for Australia. In their CGE model, aggregate changes in wages are allocated equally (in relative terms) across all labor classes, they only vary between different (Australian) regions. Hence, all households are scaled with the same wage changes and although the micro-simulation provides income changes for households in different employment categories, in fact the model does not differentiate wage increases across household types. In addition, social security benefits are indexed to the CPI, hence, there is by definition no income growth for people that receive social security benefits. At the same time, wages increase in the model, and therefore, income inequality rises through the design of the model.

4.1. Sequential (top-down) approach

In sequential MS studies, changes in labor markets, capital markets and aggregate consumption are first determined in the CGE model and then moved as exogenous variables into the MS model. The MS model is then used to determine the impacts on households, or to select those households that change labor markets (Colombo, 2010). A first set of equations in all MS models determines income, taxes, savings and expenditures for all household types, based on the survey data, the tax system and constraints from the macro-model. For arithmetic models, this is the main part of the model. A second set of equations is called 'behavioral': it is a series of econometric functions that determine household behavior based on characteristics of individuals that are observed in the household survey (Bourguignon et al., 2003). Generally, behavioral choices are focused on occupational choices of household members. Household outcomes such as occupation, income, taxes, etc. are therefore determined jointly by the first (arithmetic) and second (behavioral) elements of the model.

There is a range of potential output variables of CGE models that can be used as input for micro-simulation models to distribute the results over multiple household types (Lay, 2010). In factor markets, real wages for labor types and returns to land and capital can be used. For factor quantities, the sectoral composition of labor is most relevant. For consumption, prices of goods and the quantities consumed are the ideal candidates for linking the models.

4.1.1. Arithmetic sequential microsimulation

4.1.1.1. Description of the method. Arithmetic micro-simulation models (often called non-behavioral or accounting models) include a set of equations that determine for household types the change in income, tax levels, and Consumer Price Index (based on the household types' individual mix of goods consumed), based on changes in wage rates and prices from the CGE model. Consumption can be determined by the survey data or modeled as demand system. The arithmetic micro-simulations usually include detailed modeling of taxes and transfers, and determine gross and net income on the level of household types (Herault, 2010). The household type specific CPI is used in most studies to analyze the number of people below a poverty line.

Although most applications of this approach are performed with static CGE models, attempts exist to use (recursive)-dynamic CGE models as well (Buddelmeyer et al., 2008). In this "reweighting approach", the weight of the contribution of a household type to the total distributional output (such as income or expenses) is adjusted based on population and household projections and employment levels. For example, if projections are that the total population ages and employment shifts from agriculture to services, the weight of elderly households and households in the service sector increases, whereas younger households and agricultural laborers are given less weight in

Table 2
Main characteristics of recent papers using arithmetic micro-simulation models.

Paper	Country	CGE type	Focus	Model	Time
Ahmed et al. (2011)	Tanzania	Static	Climate variability	GTAP-POV	1971-2031
Buddelmeyer et al. (2008, 2012)	Australia	RD	GHG mitigation scenarios	MITTS (MSM) MMRF-Green (CGE)	2005-2030
Cogneau and Robilliard (2000)	Madagascar	Static	Growth shocks		
Dartanto (2013)	Indonesia	Static	fuel subsidy reform	IFPRI-model	
Devarajan and Go (2002)	Zambia	Static + RD	Macroeconomic shocks	123PRSP	2001-2003
Hertel et al. (2009)	Global	Static	Trade liberalization	GTAP-POV	
Hertel et al. (2010)	Global	Static	Climate change impacts	GTAP-POV	2030
Hertel et al. (2011)	Global	-	Macroeconomic shocks	GTAP-POV	

Abbreviations: RD: Recursive Dynamic.

the results. This is a relatively simple way to use micro-simulation in combination with a dynamic CGE model (see a discussion on reweighting vs behavioral models in Section 4.3).

4.1.1.2. Key assumptions and limitations. The arithmetic nature of this approach means that it only indicates the distributional impacts of policy changes on the households as they are characterized by the survey data and from downscaling aggregate changes in the representative household(s). Household choices, such as employment or changes in expenditure patterns, will change in line with the representative household's choices within the CGE model. Hence, the change in employment and consumption is not due to the characteristics of the individual households in the micro-simulation but only determined by the representative household in the CGE (Buddelmeyer et al., 2008).

4.1.1.3. Examples. Most applications of arithmetic sequential micro-simulation models are with static CGE models (Table 2). The examples that are most relevant for global, long-term applications are studies that reweight the samples of the original household survey into the future based on population projections. Buddelmeyer et al. (2008) describe a recursive dynamic CGE model for Australia, combined with a arithmetic micro-simulation. Both models use a similar population projection, which includes population structure in terms of age, gender and region. The results of the macro-economic model are downscaled to the level of households, and reweighted for structural changes in the population (see further discussion in Section 5.3).

The Global Trade Analysis Project poverty framework (GTAP-POV) is an arithmetic micro-simulation that can be sequentially linked to an adjusted version of "standard" GTAP CGE model (Ahmed et al., 2011; Hertel et al., 2009; Hertel et al., 2010; Hertel et al., 2011). The model structure is generic, but must draw on national household survey data (or parameterizations derived from these data) for specific analyses. The aim of the GTAP-POV structure is to perform poverty analysis for single countries, within the context of a global CGE model. It is explicitly mentioned not to aim at global poverty analysis. In this model, the poverty analysis relies on simulating household welfare at the poverty line for different segments (strata) of the population. Household welfare and the associated consumption decisions are arrived at by maximizing the household's utility function subject to their budget constraint, where the latter is influenced by their endowment composition, as revealed in household survey data. For any given level of goods and factor prices the system gives the levels of consumption demands and associated utility. Alternatively, for any change in commodity prices, it is possible to compute the expenditure required to allow a household to remain at the initial level of utility. This initial level of utility at the poverty line is defined as the *poverty level of utility*, and reflects how the 'true cost of living at the poverty line' changes over time as a result of changing commodity prices. Using this true cost of living, nominal income change arising out of changed factor prices can be deflated, to obtain the change in real income, by stratum. This change in real income coupled with information about the stratum elasticity of poverty headcount with respect to real income, enables predicting changes in poverty headcount by stratum (Hertel et al., 2011).

4.1.2. Behavioral sequential micro-simulation

4.1.2.1. Description of the method. The behavioral method was developed to identify which household types change to above or below the poverty line as a consequence of policies and development. It deals with questions as: what happens when the level and/or composition of employment changes? Which households would decide to change employment or decide to become (in)active on the labor market? What are the characteristics of these households in terms of vulnerability and poverty? Are household heads changing their employment status or is it household members?

Theoretically, it is possible to model a wide range of behavioral choices of households related to all aspects of households in CGE models (see Section 2), but literature focuses mainly on occupational choices. Behavioral micro-simulation models make an econometric estimation of the probability that a household (member) is in a certain occupation, often on the basis of (multinomial) logit models. The probability of being in a certain labor market is derived from an implicit utility function. Utility associated with each category of labor is a linear function of characteristics of an individual defined in the household survey (such as age, gender, children under six, education, etc). In theory, these models do not identify a particular labor market choice for each individual, but generate a probability distribution over the labor market choices of the whole population (Bourguignon et al., 2003; Creedy and Kalb, 2003).

The total employment level can be endogenous in both the CGE model and the micro-simulation model, albeit in different ways. Hence, a key aspect for these models is to maintain consistency between the micro-simulation and the CGE with respect to the total employment level, wage rates and income levels (Herault, 2010). Therefore, some constraints have to be imposed on the micro-simulation to maintain consistency. This is usually done by adjusting the parameterization of the econometric model that determines occupational choices, by using iterative optimization methods (such as Newton) to minimize the difference between the two models. An alternative approach is to form queues for occupational choice, e.g. queues of households that are likely to switch occupation in case employment at the macro-level would allow them so (Herault, 2010).

4.1.2.2. Key assumptions and limitations. This school of modeling traditionally has a strong focus on labor and occupational choice, even though theoretically expansion of micro-simulation to other aspects of household economic behavior such as savings or consumption is possible as well. Behavioral microsimulation is very data intensive, since it needs background data that characterize household members to define the behavioral choice modeling.

4.1.2.3. Examples. Most applications of behavioral micro-simulation models use static CGE models and focus on macro-economic crises or

Table 3
Main characteristics of recent papers using behavioral micro-simulation models.

Reference	Country	CGE type	Focus	Time
Bussolo and Lay (2003)	Colombia	Static	trade liberalization	
Bussolo et al. (2006)	Brazil	RD	trade liberalization	2001-2015
Essama-Nssah et al. (2007)	South Africa	Static	oil price shock	
Hérault (2006)	South Africa	Static	trade liberalization	
Lay (2010)	Bolivia/Brazil	Static	macroeconomic shocks	
Robilliard et al. (2008)	Indonesia	Static	macroeconomic crisis	

Abbreviations: RD: Recursive Dynamic.

shocks (Table 3). For instance, Bussolo and Lay (2003) published a model for Colombia that included individual occupational choice between four alternatives, inactive, wage-worker, self-employed, rural wage/self employed, to analyze the impacts of trade liberalization on income distribution. Essama-Nssah et al. (2007) developed a very elaborate choice model for South Africa, including sixteen alternative occupations (formal and informal work, three skill levels and agriculture, industry, service sectors) to analyse the impact of an oil price shock.

A dynamic application to Brazil was published by Bussolo et al. (2006) to study the changes in the transition from agriculture to non-agriculture workers over the period 2001-2015 as consequence of trade liberalization. This study used a reweighting approach to include the change in skill-composition of population.

4.2. Iterative (bottom-up/top-down) approaches

4.2.1. Description of the method

Iterative models are micro-simulation models from which information is fed back to the CGE model with the aim to converge to a common solution in a few steps. The information from CGE to micro-simulation is usually the same as described for sequential models, including changes in aggregate wages, prices and employment levels. The information from the micro-simulation to the CGE model can include changes in labor supply only, or can also cover changes in consumption patterns (Colombo, 2010).

Using the study of Savard (2003) as example, the CGE endogenously determines the prices, total household income, goods supply and labor demand. These are passed on to the micro-simulation model. The micro-simulation model determines endogenously household incomes, consumption, labor supply and unemployment levels (taking exogenously the prices, labor demand and wage rates from the CGE) and returns consumption and labor supply to the CGE model. Labor supply changes once households respond to new wage rates. Consumption patterns (or preferences) might in some cases also need to be adjusted in the CGE if consumption patterns change considerably if household are reclassified to a new category (e.g. from unskilled to skilled labor, endogenous urbanization, or inactive to active on the labor market). This loop is continued until the models converge on consumption and labor supply.

4.2.2. Key assumptions and limitations

According to Colombo (2010), the way of modeling feedbacks from the micro-simulation to the CGE macro is essential and influences the results. She shows that the use of shares is to be preferred over the use of absolute values to maintain consistency between the models. In addition, data inconsistencies between the micro-simulation data from household surveys and the SAM in the CGE-model can affect the results as well. This can be prevented by adjusting either the micro or the macro data, but this should be done at the stage of model development (see discussion in Section 7.2).

4.2.3. Examples

Table 4 shows several recent examples of studies the used iterative approaches. Main examples of this approach are Savard (2005, 2010), who introduced the concept of the iterative approach with an application to the Philippines. He iterates the CGE and micro-simulation model several times, exchanging information on prices and employment, until the models converge to a similar result analyzing a specific macroeconomic shock or investment.

The World Bank has developed a behavioral global micro-simulation model (GIDD) that is run together with the global CGE ENVISAGE (Bussolo et al., 2010). The starting point of this micro-simulation is a set of changes in the demographic structure. The relative size of the different age groups is modified following the World Bank's population projections. Additionally, the changes in the demographic structure have an impact on the average educational attainment and therefore, educational endowments are modified accordingly. The micro-simulation model accounts for these changes by adjusting the weight of individuals in the household survey data. This population projection is used in the runs of the recursive dynamic global CGE model ENVISAGE. The GIDD microsimulation receives a vector of changes in prices and quantities for future years and derives results at the household level. The main feature of the GIDD is that it then determines the labor reallocation, based on changes in the global CGE. Workers will choose to abandon the agricultural sector if this choice represents an increase in their expected earnings. Therefore, any change in the rate of reallocation of labor across sectors will have an impact on income distribution. The GIDD derives the probability of household heads changing from the agriculture to the non-agriculture sectors using a probit distribution based on characteristics of the household. The workers are queued based on this probability score and workers with higher probabilities to be in non-agricultural sectors are moved out of the agricultural sector up to a point where the predicted share of workers by sector

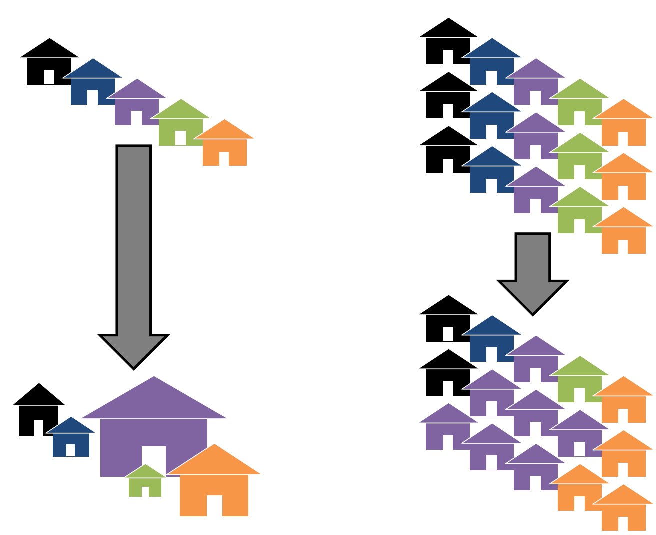

Fig. 5. Schematic representation of reweighting approaches (left) vs. behavioral approaches (right) for micro-simulation. In the left panel, the relative weight of households changes as results of structural shifts in demography or employment. In the right panel, households are reclassified.

(the macro constraint) is satisfied. The final step in the GIDD micro-simulation is to adjust factor returns by skill and sector, as well as the average income/consumption per capita, in accordance with the results of the CGE model.

4.3. Reweighting to represent structural shifts in a dynamic context

In order to deal with shifts in population structure as input to CGE models and micro-simulation models, between two periods, one can reweight the sample size of population groups. With respect to reweighting inputs, for instance, the results of certain age groups or education groups could obtain a higher weight compared to the base-year in future projections. With respect to accounting for output shifts, reweighting the results of micro-simulation in accounting models could be an alternative to behavioral models. Herault (2010) compared a behavioral approach and arithmetic/reweighting approach for a case of reducing import tariffs in South Africa (see schematic representation of the difference between these approaches in Fig. 5). In his example, the weight of different population groups (age, race, skill) is increased or decreased according to the changing pattern that the CGE model provides for labor. For instance, if employment increases in the formal sector, and reduces in the non-formal sector, the reweighting model increases the weight of, for instance, a 29-year-old high-skilled white person, working in the formal sector, and will seek to reduce the weight of another 29-year-old high-skilled white person, not working in the formal sector. This leads to different shifts in occupation than the behavioral approach, where the household type characteristics endogenously determine the most probable labor choice. Herault (2010) finds that the reweighting approach introduces a bias in labor market changes: the reweighting approach underestimates changes in distribution, but can still be used to derive an indication of the direction of change. The reweighting approach has an advantage in that it requires less data. The behavioral approach needs household characteristics to parameterize the behavioral changes.

Furthermore, the reweighting and behavioral approaches can be complimentary if the main interest is in a distant point in the future. Reweighting should then account for demographic changes of the base-population, while the occupational choice results could be derived from endogenous changes in the behavioral model. This method is applied in the ENVISAGE-GIDD model of the World Bank (Bussolo et al., 2010).

5. Direct modeling of income distribution

5.1. Description of the method

This approach assumes a relative income distribution within the single representative household type or within each of multiple household types. The mean income of the distribution corresponds to the mean income in the representative household(s) in the CGE model. The relative income distribution can be modeled based on many different functions (Boccanfuso et al., 2003) or could be fit to actual household survey data or other distribution data. The method is applied ex-post to the CGE model results; the distribution itself has no feedback influence on the results of the CGE model (Fig. 6).

5.2. Key assumptions and limitations

The results of this method depend strongly on the income data that are used. If the data have limitations, such as low quality, limited resolution or limited representation (especially at the tails), this will be reflected in the results of the study. An option to overcome data problems is to estimate a function that describes income distribution based on the data. However, there are many different options for the functional form (see Boccanfuso et al., 2003), such as lognormal, gamma, beta, or displaced lognormal, and the results of the analysis can strongly depend on the functional form that is chosen if functions differ a lot around an absolute poverty line (Boccanfuso et al., 2003).

Often, the distribution function is held constant over time and does not change if, for instance, the relative amount of income from each factor (labor, capital) evolves for the household(s). This constant distribution function might be defensible for a model with multiple representative households for short-term analyses, but is probably incorrect for a model with a single representative household and for long-term studies, when shifts in employment and income composition occur (Boccanfuso et al., 2003; Melnikov et al., forthcoming).

5.3. Examples

This work started in the 1970s with work by Adelman and Robinson (1978), later followed by the OECD research program to explore the impact of structural adjustment on equity (de Janvry et al., 1991; Morrisson, 1991; Thorbecke, 1991). More recent examples include

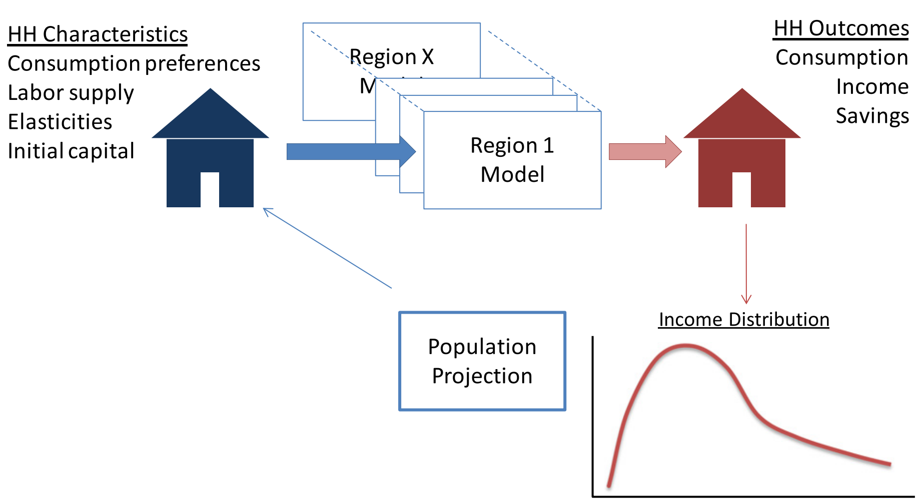

Fig. 6. Schematic representation of the direct modeling of income distribution approach.

Table 4
Main characteristics of recent papers using iterative micro-simulation models.

Paper	Method	Country	CGE	Focus	Model	Time
Ackah et al. (2009); Bussolo et al. (2008a, b); Bussolo et al. (2010)	behavioral	Global	RD	Agriculture, climate change, trade shocks	LINKAGE (CGE) GIDD (MSM)	2000-2030
Ferreira Filho and Horridge (2005)	behavioral	Brazil	Static	trade liberalization	ORANI-G	
Savard (2005)	behavioral	Philippines	Static	macroeconomic shocks		
Savard (2010)	behavioral	Philippines	Static	infrastructure investment		

Abbreviations: RD: Recursive Dynamic.

Boccanfuso et al. (2003), who analyze a series of different functional forms for income distribution within household groups and compare these to the results of a CGE model that explicitly includes all individual households from a household survey for Senegal. Analyzing different trade shocks, they find that no distribution function is best, but that more flexible functions generate results that are closer to the results of the survey data and the CGE model results. They also observe that the overall income distribution for the population as a whole changes as a result of shifts in per capita income and numbers of people across the household types in the CGE model.

Sánchez and Cicowiez (2014) used the MAMS recursive dynamic CGE model combined with lognormal income distributions to analyze distributional impacts of investments in human development, such as the Millennium Development Goals, for Bolivia, Costa Rica, Uganda and Yemen. Van der Mensbrugghe (2015) used this approach to develop long-term projections of income distribution for the Shared Socioeconomic Pathways (SSPs).

6. Hybrid methods

Hybrid approaches of the methods described above exist as well. The most common hybrid approach is to combine a relatively small number of household types in a multiple household CGE model with direct modeling of income distribution or micro-simulation, to generate results for a larger number of household types or income levels. Table 5 shows recent examples of studies the used hybrid models for analyzing income distribution implications of several different shocks.

A relatively simple example is Decaluwé et al. (1999) who combine a multi-household CGE model with six household types with a direct income distribution method to analyze an archetypical African economy. The advantage of this approach is that it captures the general equilibrium effects between larger categories of households within the CGE model.

Lofgren et al. (2003) provide a description of a static CGE model with several representative households (which is in other studies referred to as the IFPRI-model). Outcomes for each household type are used as input to an arithmetic micro-simulation model. The CGE model generates incomes (total and disaggregated by source), consumption (mean quantities, prices, and mean values), and factors (mean employment, wages or rents), and mean incomes for each household type. These feed into a sequential arithmetic micro-simulation model, allocating each survey observation to a household type in the CGE model, to determine the within-type distribution. This model has been applied in other studies as well, for instance to analyse impacts of carbon taxes in Vietnam (Coxhead et al., 2013) and tax reforms in Mexico (Debowicz and Golan, 2014).

Table 5
Main characteristics of recent papers using hybrid methods for modeling income distribution.

Reference	Method	HH types in CGE	Region/Country	CGE	Focus	Model	Time
Decaluwé et al. (1999)	Multi-HH + distribution	5; R: small landowner, large landowner, U: low-edu, high-edu, capitalist	Archetypical African	Static	trade shocks		
Debowicz and Golan (2014)	Multi-HH + iterative behavioural MSM	16 + MSM	Mexico	Static	tax reform	IFPRI-model	
Coxhead et al. (2013)	Multi-HH + sequential arithmetic MSM	20; U/R, occupation, quintiles	Vietnam	Static	carbon tax	IFPRI-model	
Arndt et al. (2011)	Multi-HH + sequential arithmetic MSM	20: U/R, gender, quintiles	Mozambique	RD	bioenergy production		2003-2015
Arndt et al. (2012)	Multi-HH + sequential arithmetic MSM	15; R: farm, nonfarm and U: nonfarm, by quintile	Tanzania	RD	bioenergy production		2007-2015
Breisinger and Ecker (2014)	Multi-HH + sequential arithmetic MSM	8; U/R + AEZ	Yemen	RD	Food consumption and malnutrition		2010-2020
Lofgren et al. (2003)	Multi-HH + sequential arithmetic MSM	Several	None	Static	-	IFPRI-model	
Pauw and Thurlow (2011)	Multi-HH + sequential arithmetic MSM	110; U/R, farm, non-farm, quintiles	Tanzania	RD	agricultural growth		2007-2015
Pauw and Leibbrandt (2012)	Multi-HH + sequential arithmetic MSM	162	South Africa	Static	minimum wages	STAGE	
Thurlow et al. (2015)	Multi-HH + sequential arithmetic MSM	15; R: farm, nonfarm, U: nonfarm, by quintiles	Tanzania	RD	bioenergy production		
Verikios and Zhang (2013)	Multi-HH + sequential arithmetic MSM	8; RH per region	Australia	RD	power sector reform	MMRF	1990-2000
Verikios and Zhang (2015)	Multi-HH + sequential arithmetic MSM	8; RH per region	Australia	RD	urban transport reform	MMRF	1990-2000
Vandyck and Van Regemorter (2014)	Multi-HH + sequential arithm. reweighting MSM	3; RH per region	Belgium	RD	energy taxes	GEM-E3	2050
Estrades and Terra (2012)	Multi-HH + sequential non-parametric MSM	10; income deciles	Uruguay	Static	macroeconomic shocks		

Abbreviations: U: Urban, R: Rural, Ag: Agriculture, inc: income, self-emp: self-employed, AEZ: agro-ecological zone, RD: Recursive Dynamic.

Table 6
Overview of differences between methods for including income distribution in CGE models with respect to applications and data needs.

Method	Application in climate change research	Data need
Multiple household types	Income distribution scenarios, full impacts of climate change and climate policy for different HH types including interactions between HHs and macro	Medium: HH type level information on income and expenditures
Arithmetic micro-simulation	Income distribution scenarios, full impacts of climate change and climate policy for different HH types with focus on social tax/benefits differences	High: specific information on tax and benefit system
Behavioral micro-simulation	Income distribution scenarios, full impacts of climate change and climate policy for different HH types and labor force/poverty response	High: specific information on household characteristics
Direct modeling of income distribution	Scenarios of number of people/HHs in poverty	Low: distribution of income within HH types

7. Data availability and handling

7.1. Databases

The World Bank provides several databases containing income distribution information. For the GIDD tool (see Section 6.3), the underlying data are made available for wider use in excel/stata databases. These databases can be found at http://go.worldbank.org/YADEAFEJ30. These databases contain income/consumption level information for vintile groups of population (5% incremental) for 116 countries, covering 91% of the world population (Ackah et al., 2009). For a smaller set of countries (73 countries), the database also includes the other variables that are used in the GIDD micro-simulation model: age, education level, household size, urban/rural, agricultural occupation, share of food expenditures and gender. These data are all aggregated to the vintile level, the raw survey data are not published here. This data could be used to construct income distribution curves for ex-post analysis of CGE results.

When full household survey data are needed to characterize the households in the model, another class of databases on available household surveys, such are the World Bank Central Microdata Catalog (http://microdata.worldbank.org/index.php/catalog/central) and the International Household Survey Network (www.ihsn.org). In both databases, one can search specifically for certain surveys for particular countries and years, or for surveys containing a specific variable in the questionnaire. This should provide information on which surveys and data are available, and the raw data must then be obtained through national statistical agencies. These data can be used to characterize multiple households in the CGE model (in terms of assets, income and expenditures) or to build a micro-simulation model to simulate the impacts on many households. Several attempts at harmonization across countries have been made (see e.g. Frick et al., 2007), and for limited sets of countries, consistent databases are available, such as the Luxembourg Income Study Database (LIS) (2015).

7.2. Adjusting the Macro-economic data or the microeconomic Survey data

Consumption levels and incomes can deviate substantially between survey data and data from national accounts (Deaton, 2001; Deaton and Kozel, 2005). Differences can amount to the order of 50%, with a general pattern that household survey data have lower incomes and expenditures than national accounts data. Several arguments are used to explain the difference between these data sources (Deaton, 2001). The three main arguments are 1) that household respondents tend to under-report income and expenditures in surveys, to hide part of their income for taxes and 2) that household surveys under-represent richer households. Third, household consumption is a residual-category in the methodology for national accounts, where intermediate and final consumption of industries and governments are 'measured', households are the residual category that is influenced by reporting errors in the other sectors.

When combining information from national accounts and household surveys in a single model framework, one has to decide to scale either one or the other to maintain consistency within the model. In general, one could argue for one or the other, see for instance discussion in Colombo (2010) or Herault (2010). Global CGE models, however, often use data from the Global Trade Analysis Project (GTAP) (Narayanan and Walmsley, 2008) which provide globally balanced and consistent input-output tables and international trade data. Therefore, in these applications the only realistic option is to adjust the survey data to the GTAP data. First, in a global model it is not possible to scale the global GTAP data consistently to surveys for multiple countries/regions in parallel. Second, scaling the GTAP data would be much more work, and influence model results more than scaling the survey data would. A last issue worth mentioning is that data in the survey are generally classified by expenditure classes (housing, transport, tourism, etc.) while national accounting data are categorized by commodities like oil

Table 7
Overview of inputs, outputs, data requirements and interactions between households and macro-economy for different methods for modeling income distribution.

Method	Inputs	Outputs	Data needs	Interaction
Multiple household types	N/A (same as CGE model)	Similar to the outputs of the CGE (income, consumption, labor (if endogenous) but at the level of household types, or aggregated to indices or distributions.	Household survey with household level data on: 1) expenditures on goods, 2) wages and capital income 3) assets and demographic projection on changes in HH characteristics	Full interaction between HH types and macro-economy within CGE model
Arithmetic micro-simulation	(Changes in) wages, prices and employment level (if unemployment is modeled) from the CGE model	(Distribution) of HH income, (Distribution) of HH expenditure, Distributional indicators, such as headcount and GINI index	HH level information on taxes paid, social benefits received, hours worked. Taxes and benefits system information to determine eligibility for benefits and consequences of changes in earnings for tax payments.	No interaction between HH types. Interaction between HH types and macro-economy possible through iterations
Behavioral micro-simulation	(Changes in) wages, prices and employment level from the CGE model	Occupational choice of individuals/HH, (Distribution) of income, (Distribution) of expenditures, Distributional indicators, such as headcount and GINI index	Information on the HH characteristics and HH members: e.g. age, gender, qualification, education, children under six, etc. Needed to model occupational choice and response to macro-changes	Interaction between HH types and between HH types and macro-economy possible through iterations
Direct modeling of income distribution	Mean income change for representative household(s) in CGE model. Price changes and consumption patterns if needed to calculate CPI	Number of people/HH in specified income categories. Number of people/HH below poverty line. Distributional indicators, such as headcount and GINI index	Household surveys or more generic databases that enable the parameterization of a distribution function of household income over population or households.	No interaction between HH types nor between HH types and macro-economy

(that could be either for housing or for transportation for example). This will make the data reconciliation procedure more difficult (see also Zigova et al., 2009).

8. Discussion and conclusion

This paper presents an overview of methods to include income distribution modeling in CGE models, with an emphasis on global long-term environment-economy models. The methods that were discussed have varying requirements for data, and can produce heterogeneous results for a range of model outputs while taking into account different interactions between household types and the rest of the economy (Table 7). Multiple household CGE models only require a change in the number of household types in the CGE model and produce heterogeneity in all household-related outputs of the model while taking full interaction between the household types and the macro-economy into account. Micro-simulations can provide detailed outcomes for a large number of household types but do not cover interactions between households. Direct modeling of income distribution can be done with limited data available, but does not deal with structural changes in future projections or any interactions between households and or with the macro-economy.

Most of the existing literature focuses on poverty analysis, mainly studying the impacts of changing trade policies or labor regulations. As a consequence, most work has been done on heterogeneity in labor supply (and less on capital, since this is less relevant for households close to the poverty line) and overall changes in the CPI to account for purchasing power impacts of policies (and less on detailed responses in consumption patterns). For long-term scenarios and climate change related applications, heterogeneity in capital endowment and accumulation becomes more relevant as well as differences between household types in consumption patterns and responses to price changes. Both of these may require methodological developments beyond the current applications of these methods in (mainly) static models.

The different methods that we discussed in this paper have different potential applications in climate change related research (Table 6). The simplest method, static income distribution, would help developing scenarios for future population in poverty, which is a major aspect of vulnerability to climate change impacts. Including multiple household types in the CGE model would enable producing scenarios for future income distribution changes as result of changes in household composition and macro-economic developments. It would also enable analyzing the full impacts of climate change and climate policy on different household types, including the interactions between households and between households and the macro-economy. The micro-simulation methods, which can be developed relatively independently from the CGE model, have slightly different potential applications. Through iterations with the CGE model, they could 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. Arithmetic micro-simulations enable developing income distribution scenarios and account for the full impacts of climate change and climate policy on different household types. Behavioral micro-simulation methods add to this that they (traditionally) account for changes in the labor force decisions of households and individuals and can help analyzing scenarios for changes in vulnerability of the population to climate change impacts.

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