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Guide to Microsimulations Linked to CGE Models: How to Introduce Analysis of Poverty and Income Distribution in CGE-based Studies

Version 2

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ABSTRACT

Micro-macro syntheses have become a powerful tool to capture the micro effects of macro policies and external shocks on income distribution and poverty. The range of techniques is wide and their implementation will depend on the objectives of the study, the availability of time and data, and the compatibility with the macro model applied. In this guide, we present the different techniques and briefly describe their pros and cons. We also present detailed instructions on how to implement two microsimulation techniques: a non-parametric microsimulation model and a representative household model. We obtain similar results on poverty using both methods to analyze the impact of trade liberalization in Tanzania. This is due to the underlying CGE model assumptions of fixed employment level and perfectly mobile labor. When we introduce unemployment, we obtain more pronounced results under the non-parametric microsimulation model.

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1. Introduction

The transmission of trade policies and external shocks to poverty occurs through several complex and diverse channels; in some cases, we find direct and indirect effects that operate in opposite directions. Thus, using a methodological tool to capture these diverse channels of transmission is extremely necessary. The tool currently most widely applied is a combination of macro models and micro models known as "macro-micro synthesis." The macro model component, usually a computable general equilibrium (CGE) model, accounts for impacts of trade policies and external shocks on macro variables and the labor market. However, this method is insufficient to account for impacts at the household level and to analyze the effects on income distribution. To address this gap, micro models, which incorporate detailed information at the household level, are then linked to the macro model. This document presents the "macro-micro synthesis" in more detail using a specific example from Tanzania.

The macro-micro synthesis is the most efficient tool available to analyze the links between impacts on macro and micro variables. This method captures most of the channels through which trade policies and external shocks affect the economy at the macro level (change in relative prices of goods, impact on labor market, change in relative factor remuneration, change in government revenue, change in consumption pattern by households, etc.) and at the same time incorporates micro data that accounts for distributional impacts at the micro (household) level. The integration between the macro and micro levels is necessary because, as Bourguignon *et al.* (2008) point out, micro models alone cannot explain changes in poverty due to macroeconomic policies such as trade reforms and public spending policies, while macro models do not account for the poverty and distribution effects of policy changes at the household level.

The range of macro-micro techniques is diverse and has developed substantially in recent years. These techniques differ in the way macro and micro models are integrated (from top-down approaches applied in a sequential fashion to full integration of the micro model within the macro model), the type of micro model considered (behavioral models, non-parametric approaches, or representative households models), and the type of macro models applied (CGE, partial equilibrium, or econometric models). The next section presents the different techniques that are currently most widely applied, focusing on the links between micro models and CGE models. However, it should be taken into account that inputs from other macro models can also be fed into micro models, especially microsimulation models.[1] Table 1 summarizes the advantages and disadvantages of the different approaches.

2. Macro-micro Synthesis

The first and simplest approach to compute the effects on poverty and income distribution using CGE models is to expand the number of representative households in order to account for different earning patterns. The disaggregation usually attempts to reproduce the existing socioeconomic stratification by distinguishing homogenous population groups. At the same time, characteristics

[1] However, using partial equilibrium and econometric models limits the type of inputs that can be fed into the micromodule. For example, labor market inputs are ruled out. Notwithstanding, information on prices could be more detailed.

are ideally stable and derivable from existing data sources (Decaluwe *et al.* 1999). The three most commonly used criteria to disaggregate households in a Social Accounting Matrix are geographical location, resource endowments and wealth, and occupation of household head (Thorbecke 2000). Disaggregation by income level is usually avoided because income level is an endogenous characteristic to the model. However, for cross-sectional comparisons, it can be a useful criterion (Round 2003).

While in this case, results on income distribution are accounted for between groups, the approach does not account for changes within groups, which can be even more important, as Agenor *et al.* (2003) show. This problem is minimized by increasing the number of representative households; however, as Piggot and Whalley (1985) find, even with a high number of households (they consider more than 100 households), there are still important intra-group heterogeneities that the technique does not account for. To overcome these problems, several methods have been developed that combine the macro model with a micro module that integrates micro data at the household level. These approaches include an integrated approach, a representative household approach, and layered approaches.

2.1. Integrated Approach

The first option is to move from "representative" to "real" households in the CGE model; that is, to integrate the household survey into the CGE model so that the model includes as the same number of households as the household survey sample. This methodology was applied by Cockburn (2001) for Nepal (3,373 households), Cororaton (2003) for the Philippines, and Boccanfuso and Savard (2007; 2008) for Mali (4,966 households) and Senegal (3,278 households). The main drawback of this methodology is that it substantially increases the computational efforts of the standard CGE models and might present data reconciliation problems. Therefore, other techniques have been more widely used to estimate the effects on poverty and income distribution. These can be roughly divided in two groups: the representative household (RH) approach and the microsimulation, or layered, approach (MS), although each one "covers a potentially wide range of alternatives with overlapping boundaries" (Lofgren *et al.* 2003).

2.2. Representative Household Approach

The representative household approach, as presented in Lofgren *et al.* (2003), consists of feeding data on the CGE results for the representative households (RHs) into a separate module that contains additional information about each RH. The authors propose two different alternatives to this approach: i) assuming a distribution function in order to compute income distribution within groups and ii) feeding the CGE results on a household disaggregated data (which is in turn consistent with the SAM used to calibrate the CGE).

Respecting the first alternative, several papers have identified the most adequate distribution function. The most commonly used is the lognormal frequency function (in Adelman and Robinson 1978, Dervis *et al.* 1982, and others), while other authors suggest the Pareto distribution (de Janvry *et al.* 1991) or the more flexible Beta distribution function (Decaluwe *et al.* 1999)[2]. The parameters of the distribution functions are estimated with household survey data (this is the only instance in which household survey data is used in this procedure). The main drawback of this method, known as the "distribution function approach", is that it relies on approximated income distribution as opposed to real income distribution; thus, results will rely on the quality of the estimates of shape parameters (Agenor *et al.* 2004).

The second alternative assumes that each RH is representative of all households in its group; thus, the survey can be fed with data both on income by RH and on commodity prices in order to compute the changes in real income for all households of the survey, as well as to also adjust the value of the poverty line. In this case, the observed income distribution for the sample of actual households is taken into account. In this way, the method poses an advantage as compared to the distribution function approach. The main drawback of this method, also known as the "micro-accounting approach", is that it assumes that within-group distributions are unaffected by the shocks under consideration. It also disregards changes in employment at a macro level, as individuals are assumed to stay in their initial activity. If the model is dynamic, this approach does not take into account other changes such as the change in population structure by age and rural/urban structure. These drawbacks lead to significant underestimation of changes in income distribution (Bourguignon *et al.* 2003). However, the method is still attractive because of its simplicity and because it captures the largest impact of reforms (Bourguignon *et al.* 2008).

A variant of this approach is what Agenor *et al.* (2004) call the "reweighting method", a procedure that includes changes in employment structure. The authors suggest three dimensions: rural/urban, agriculture/formal/informal, skilled/unskilled; however, the method could be improved by adding new dimensions, such as age and gender. This procedure reweights the household survey sample, holding the underlying characteristics constant. Income distribution within groups changes with this approach to the extent that population and income shares of each group change over time (Agenor *et al.* 2004). As Agenor *et al* (2004) show, when the simulated shock has an impact on employment, applying re-weighting techniques significantly modifies the poverty results as compared to the simple micro-accounting approach and the distribution function approach. The drawback is that changes in employment are incorporated by changing the weights of individuals without taking into account behavior. This last element is incorporated in microsimulations, which will be presented in the next session.

2.3. Microsimulations

The main difference between top-down micro-accounting methods and top-down microsimulation methods is that the latter incorporates behavior response through an econometrically estimated behavior model (behavioral microsimulations) or by assuming that the occupational changes are proxied by a random selection procedure (non-parametric microsimulations).

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[2] Boccanfuso *et al.* (2008) test seven alternative continuous distribution functions (lognormal, gamma, beta, champernowne, displaced lognormal, Singh-Maddala, and Dagum) and one non-parametric method for Senegal and conclude that the most adequate functions are the most flexible ones (such as the Beta distribution function).

As in micro-accounting methods, top-down microsimulations are applied in a sequential fashion, taking parameters from the CGE model[3] and feeding them into the micro module without any further interaction between the macro and the micro levels. This approach has been most widely applied in two variants: a) behavioral microsimulations and b) non parametric microsimulations.

The behavioral approach, as presented in Bourguignon *et al.* (2001) and applied in several works (Chen and Ravallion 2003, Bourguignon *et al.* 2002, and Bussolo and Lay 2003, among many others), consists of modeling the income generation process of households by estimating a series of equations using household survey data. The income generation model entails an earning model and an occupational choice equation. Household real income is specified as a non-linear function of the observed characteristics of household members (age, education, etc.), some characteristics of the household, its budget shares, and unobserved characteristics. This function depends on four sets of parameters: parameters in the earning functions for each labor market segment; parameters of the self-employment income functions for the different sectors; parameters in the utility of the alternative occupational choices for the various demographic groups; and the vector of prices. These parameters are taken from the CGE model and are fed into the micro-simulation module.

The main advantage of this method is that it explicitly models behavior responses from households and accounts for changes in employment status, which are found to have the highest weight in changes in income distribution. However, this method is difficult to implement and creates doubts about the robustness of the parameters estimated (Vos and Sanchez 2010), as well as about theoretical and empirical inconsistencies with the macro model (Lay 2010). In addition, in a comparison of this method to non-parametric and RH methods (to which the author refers as non-behavioral and arithmetic methods, respectively), Debowicz (2011) does not find significant differences between behavioral and non-behavioral microsimulations for poverty and income distribution results. As the RH approach does not take changes in employment into account, it provides very different results on poverty and income distribution, in most cases with opposite sign. However, if changes in employment are not accounted for in the macro model, results from the RH approach do not differ significantly from other microsimulations. Herault (2010) compares results from applying a behavioral microsimulation approach and an RH combined with a reweighted sample (known as "reweightening method"). Even when the reweightening method underestimates distributional changes, the author does not find significant differences between the approaches, which leads to the conclusion that the reweightening approach might be a good alternative given its simpler implementation.

Non-parametric microsimulations partially overcome some of the drawbacks of behavioral microsimulations, mainly because the method is easier to implement. This approach was developed by Ganuza *et al.* (2002) and applied in Vos *et al.* (2006) and other studies. The underlying assumption of this method is that occupational shifts can be proxied by a random selection procedure within a segmented labor market structure. This procedure allows for the imposition of counterfactual changes in key labor market parameters (participation rate, unemployment, employment composition by sector, wage structure, and so on) on a given distribution derived from household survey data, sequentially and randomly.

[3] In the case of top-down microsimulations, parameters can be taken from partial equilibrium models or econometric estimations. Contrarily to CGE models, however, these macro models do not provide information on the labor market, so their scope is more limited.

Labor parameters for which we impose changes are consistent with the macro model: if the model does not include unemployment, then no changes in unemployment are simulated at the micro level. The counterfactual changes in parameters follow a sequence with the idea that changes in the labor market follow a non-neutral order. The commonly accepted sequence is the following: first, the person decides whether or not to participate in the labor market; second, the market decides whether or not that person will be employed; finally, the person decides in which sector to work, which determines a certain wage level and, in the aggregate, the average wage of the economy.

Random numbers are used to determine which persons of working age change their labor force status, which change occupational category, which employed persons obtain a different level of education, and how new mean labor incomes are assigned to individuals in the sample. Hence, the assumption is that, on average, the effect of the random changes correctly reflects the impact of the actual changes in the labor market. Because of the introduction of a process of random assignation, the microsimulations are repeated a large number of times in Monte Carlo fashion. This allows for constructing 95% confidence intervals for the indices of inequality and poverty, except in the case of the simulations of the effect of a change in the structure and level of remuneration; these simulations do not involve random numbers. This method is easier to implement than the behavioral approach, but the main drawback is that the sequence chosen to simulate changes in the micro module may affect the results ("path-dependency").[4]

One of the main criticisms of top-down microsimulations – both non-parametric and behavioral approaches – is that they lack feedback effects from micromodule to macromodule. In effect, we might expect that changes in household behavior due to macro shocks may have an impact on macro variables as well. This is the underlying assumption behind the top-down/bottom-up microsimulation approach: changes in consumption and labor supply obtained in microsimulations are transmitted back to the CGE model, which is run in turn; then results on prices (goods and factors) are fed again to the microsimulation model. This procedure is run in loops between the two models until a convergent solution is found (Savard 2003; 2005). Even though this approach appears to provide a more coherent methodology between the macro model and the micro model, it has not been widely applied because of its complexity (it has been applied by Avitsland and Aasness 2004 and Ferreira Filho and Horridge 2006, among other authors). Another weakness of the model is that the way in which feedback effects are transmitted back into the CGE model, as well as data inconsistencies between macro and micro models, can affect results (Colombo 2010).

3. Macro-micro Synthesis in Dynamic and Global Framework

Most of these techniques are applied to single country studies (in some cases even to regions within a country) and in a static framework, although more recently there have been efforts to expand the different frameworks to dynamic models and/or to global models. The procedure for, and difficulties of, applying the behavioral microsimulation approach in a dynamic setting are presented in Bussolo and Lay (2003). The wage equation changes in this context because now

[4] In spite of this, the sequence most commonly used and accepted has an economic logic: first, the individual decides whether or not to participate in the labor market; then he/she finds a job, which determines his/her condition of employment or unemployment; this job is in a determined sector in which the individual receives a certain wage level.

wages also have a temporal determinant. The non-parametric approach in a dynamic setting has been applied in Sanchez (2004) and Vos and Sanchez (2010), among other works. In this context, the methodology makes some not very realistic assumptions – for example, that the population structure (such as aging) remains unchanged during the whole simulation period.

At the global level, we can highlight three different initiatives. First, the Global Income Distribution Dynamic (GIDD) model, developed by the World Bank, links a global CGE model, LINKAGE, with household surveys from 121 countries through a top-down behavioral microsimulation. In order to consider the dynamics of demographic changes, before being fed with results from the CGE model, the household surveys are re-weighted with exogenous demographic projections and with "semi-exogenous" projections of skill levels.[5] Changes in labor supply estimated at this stage are introduced in the CGE model. Then the usual top-down behavioral microsimulation method is applied, feeding results from the CGE model into the microsimulation model for each country. The approach was used to analyze the poverty impact of eliminating agricultural distortions (Bussolo *et al.* 2010), of climate change (Bussolo *et al.* 2008), and of rising food prices (Dessus *et al.* 2008).

Second, GTAP-POV is a module that links the GTAP CGE model with microdata from household surveys (Hertel *et al.* 2011). Within this framework, which so far has incorporated a limited number of countries, different strata of households are identified according to sources of income in each country. The model incorporates an AIDADS demand system to estimate the expenditure required for households in each strata to remain at the initial level of utility after commodity prices change.[6] This initial level of utility is used to obtain changes in real income by stratum. Using stratum elasticities of poverty headcounts with respect to real income, variations to poverty headcounts by stratum in each country are estimated. This method has been applied by studies that analyze the impact of the Doha development agenda on poverty (Hertel *et al.* 2009) and the impact of climate change (Hertel *et al.* 2010) and climate volatility (Ahmed *et al.* 2009), among others (see Hertel *et al.* 2011 for a full list of studies).

Last is an initiative by IFPRI, which integrates household disaggregation within a global dynamic CGE model, MIRAGE, for a flexible number of developing countries (MIRAGE-HH) (Bouet *et al.* 2010; 2012). In the first step, which is done for all countries in the model, the representative agent in the model is split into a private and a public agent. Then the private agent is disaggregated into a variable number of households for each country considered in the analysis. To do this, the authors use microdata from household surveys and apply a clustering procedure that groups households from the survey into groups according to their consumption pattern, their income pattern, and their per capita income. The authors show that by using this method, the inter-household income variance is minimized, which guarantees homogenous household groups in terms of income distribution.

This approach explicitly models household behavior within the model so that the responses of the different households to trade policies are fully captured at the CGE level. Another advantage of

[5] Education characteristics by age group are considered exogenous, as the method assumes that individuals of a certain age group at moment t will maintain the educational level at t+1.

[6] AIDADS ("An Implicit Direct Additive Demand System") is a more flexible demand functional form than the more widely applied LES demand system. Unlike LES, which defines a fixed basket of basic goods for households, AIDADS do not restrict substitution of consumption goods of household below the poverty line when prices change. This feature is a key element of GTAP-POV model.

this method is that the microdata is fully reconciled with data from the CGE model, which is one of the main critiques of macro-micro models. The model better captures the behavior of the public agent in terms both of revenues collected and of expenditures, and it also endogenizes private inter-households transfers, which may play an important role in the case of trade reform. To our knowledge, this is the first global CGE model with household disaggregation. This method has been used to analyze the impact of global trade liberalization on poverty in five developing countries: Brazil, Pakistan, Tanzania, Uruguay, and Vietnam (Bouet *et al.* 2012).

Table 1: Overview of Micro-macro Techniques

Method	**Pros**	**Cons**	**References**
1. Integrated Approach	Fully integration of micro data into macro model	Computational efforts; data compatibility	Cockburn 2001, Cororaton 2003, Boccanfuso and Savard 2007; 2008
2. Representative household approach			
2.1 Distribution function	Accounts for income distribution within representative households	Results rely on the distributional form selected	Adelman and Robinson 1978; Dervis *et al.* 1982; de Janvry *et al.* 1991; Decaluwe *et al.* 1999 ; Boccanfuso *et al.* 2008
2.2 Micro-accounting method	Simplicity; Provides similar results to layered approaches if the macro model does not account for changes in employment	Does not take into account changes in employment	Agenor *et al.* 2004; Lofgren *et al.* 2003; Bussolo *et al.* 2008
3. Microsimulations			
3.1Top-down/Bottom-up	Includes feedback effects from micro behavior back to macro model	Results are affected by the way feedback effects are transmitted back into the CGE model, and by data inconsistencies between macro and micro models	Savard 2003; 2005
3.2 Top down			
3.2.1 Behavioral microsimulations	Identifies clearly winners and losers from changes in employment and unemployment	Complexity	Bourguignon *et al.* 2001
3.2.2 Non-parametric microsimulations	Simplicity; Provides similar results to behavioral microsimulations	Does not take into account individual characteristics; May underestimate changes in income distribution	Ganuza *et al.* 2002

4. Application

The choice of microsimulation technique will depend on the data available and the macro model used. The advantage of top-down microsimulation is that there is no need to reconcile data from the macro model with data from the household survey. For this reason, it is a recommended technique if there is no high household disaggregation in the model or if the input variables are taken from other sources (e.g. change in consumption prices estimated using econometrics). If we work with a CGE model that includes a high level of household disaggregation, and the households in the household survey can be identified with one of the representative households in the model, then a micro-accounting technique would be the most simple microsimulation method to apply. This method is also recommended if the macro model does not report changes in employment. In this section, we present a detailed step-by-step procedure for how to implement 1) a top-down non-parametric microsimulation and 2) a top-down micro-accounting method. We illustrate both methods with an application to Tanzania, applying a single-country CGE model to achieve macro results.[7]

4.1. Top-down Non-parametric Microsimulation

The microsimulation approach shown in this example allows for introducing changes in the following parameters: unemployment rate (by skill), employment rate (by sector and skill), occupation structure, wage rate (by sector and skill), average wage, average capital remuneration, and education level. The number of sectors and skill level can be easily modified according to labor market segmentation and the information available in the household survey. There is also the option of adjusting transfers; this should be done before running the microsimulations. As Vos and Sanchez (2010) explain, no randomized procedure needs to be applied in this case, provided that the households that benefit (lose) from an increase (decrease) in transfers can be identified. Poverty line values (basic poverty and extreme poverty lines) are adjusted according to changes in consumption prices from the CGE model. Computation of poverty indicators takes into account the household's new level of income after changes in labor market parameters and transfers and poverty line values. If a household's income is below the poverty line, it is classified as poor.

Changes to the following files are to be introduced before being run:

1) database.do

2) simul.do

3) master.do

1) In database.do we prepare the microdata from the household survey. The necessary changes are detailed in the .do file itself. It is important to keep in mind that changes to microdata should follow the structure of the macro model applied. That is, the segmentation of the labor market (by skills and/or by sector) will follow the macro model structure as long as information is available in the household survey for doing so (e.g. the CGE model may report detailed

[7] Files to run both procedures are available to AGRODEP members and can be run using Stata. The non-parametric microsimulation files are a modified version of syntax from Cicowiez (2006).

employment by sector but the household survey may include information on more aggregate sector level). The following categories have to be defined:j: Skill levels (e.g. unskilled/skilled)

l: Sectors of activity (e.g. agriculture/non-agriculture; agriculture/industry/service; formal/informal; etc.)

o: Occupation (e.g. wage-earners/self-employed)

This microsimulation approach also allows for updating poverty lines (poverty and extreme poverty line) according to changes in prices reported by the macro model. This is done in database.do. Changes in transfers can also be modified in this step (in transfers.do). When we run the baseline scenario, the line that calls transfers.do must be annulled and poverty line values should be set to benchmark values. Once simulation scenarios are run, we activate the line that calls transfers.do and we update poverty line values, which will be used to calculate poverty indicators as indicated above.

2) In simul.do, we feed the code with changes from the macro model. The following changes are taken into account: unemployment rate, employment rate by sector and skill level, occupation category, wage by sector and skill, average wage, average capital remuneration, and education level by sector. If the CGE model does not report changes in one or more of the variables (e.g. unemployment rate), then we write 0. The dimension of the matrices that report variable variation should be adapted according to the definition of categories j, l, and o.

3) All files are run from a single file, master.do. In this file, we specify the root directory, the number of iterations (usually 30 is enough), and the type of microsimulation (sequential or cumulative), as shown in Figure 1. Sequential microsimulation introduces each change in labor market parameters on the original database, while cumulative microsimulation takes into account changes in previous variables on the counterfactual database.

Figure 1: Choice of Microsimulation Type in master.do

```
*----------------------------------------------------------------------*
*  CHOICE MICROSIMULATION TYPE                                          *
*----------------------------------------------------------------------*

* Microsimulation type
* microsim=1 => sequential
* microsim=2 => accumulative

global microsim = 2

if $microsim != 1 & $microsim!= 2 {

  display as error "error... only two types of simulations are allowed" /*
  */ _newline "global microsim = 1 => sequential" /*
  */ _newline "global microsim = 2 => accumulative
  exit 198
}

*----------------------------------------------------------------------*
```

<u>Files to run</u>

First, the base year case should be run. This is done by setting iterations=1 in **master.do** (see Figure 2), all rates of variation to 0 in simul.do, no change in transfers in database.do, and original poverty lines in **database.do**.

Figure 2: Choice of Number of Iterations in master.do

```
* number of iterations

local iternum = 30

* IMPORTANT!
* NO data is inputted as % (i.e. 1 = 100%)

forvalues ii=1(1)`iternum' {
```

Second, we modify **simul.do** to introduce change in variables from the CGE model and set iterations = 30 (or the number we want to include) in master.do. At this stage, we can also modify poverty lines according to changes in prices reported by the CGE model. Another possibility is adjusting poverty lines in a third step in order to disentangle the impact of changes in labor market parameters and consumption prices. Finally, we can also activate the line "do transfers.do". If we do so, we should also modify **transfers.do** in order to introduce changes in transfers and to identify which households receive these changes.

The rest of the files should not be modified.

Results are obtained in folder output: in microsim.csv, we obtain results for all indicators for each iteration, while in intervals.log, we obtain results for each step and confidence intervals.

4.2. Micro-accounting Method

The micro-accounting approach follows a similar procedure to the non-parametric microsimulation but without assigning random numbers to households. For this reason, it is necessary to link each household from the survey to a representative household in the model. The main assumption is that there are no intra-group changes in income distribution. This is why it is important to have as many representative households as possible and for income distribution within the group to be homogenous. The following steps should be applied:

1) Identify the different households in the survey in order to match household included in the SAM;
2) Match income sources from the household survey with income sources from the SAM;
3) Compute poverty and income distribution indicators;
4) Check homogeneity of households in terms of income distribution;
5) Import results from CGE model;
6) Assign percentage variation to income by sources and to poverty lines; and

7) Compute new poverty and income distribution indicators.

This is done from one single do file (called RH_microsim.do in our example).

4.3. One Specific Example: Tanzania

In order to illustrate both methods, we present an application to a specific country and database. We use the IFPRI standard CGE model to simulate a 50% fall in export prices in Tanzania. The model is calibrated with Tanzania SAM for the year 2001 (Thurlow and Wobst 2003). In order to run microsimulations, we use the Tanzania Household Budget Survey 2000/2001.

We apply both methods to analyze the same shock and compare the results. We work with two labor market closures: with and without unemployment. In order to introduce unemployment, we introduce a wage curve that negatively relates wages and unemployment for unskilled and medium-skilled workers (Blanchflower and Oswald 1995).

In order to run microsimulations, we identify the following categories of workers:

u: Employed/ unemployed. As reported unemployment in Tanzania is very low, we consider self-employed without employees as unemployed in this exercise.

j: Unskilled (unfinished primary education), Medium-skilled (unfinished secondary education), and Skilled (finished secondary education).

l: Sector of employment: Agriculture/Industry/Services. Information included in the household survey about the sector of employment is not detailed and does not allow for a higher disaggregation (which could be introduced, as the SAM includes 43 sectors of activity).

No category on occupation status was defined.

Table 2 presents results obtained with both methods with a full employment labor market closure. Values at the benchmark vary slightly because of some transformation to data made by each method. For example, in the top-down microsimulation approach, we drop observations for which we do not have the necessary information to carry out microsimulations, and we restrict the sample to individuals of working age.

We obtain similar poverty results by applying both methods. This is due to the fact that in our CGE model, we do not have changes in employment level and labor is perfectly mobile, so there is only one average wage per type of labor. Poverty increases because living costs increase (food prices increase 2.7% and general prices increase 3%), while unskilled and medium-skilled wages fall (the fall is more pronounced for unskilled wages at 7.6%).

Results obtained from the micro-accounting approach are higher. This is an expected result; as the micro-accounting method assigns the average increases in wages to all individuals in the sample, results are usually overestimated when applying this method.

Table 2: Comparison of Results Obtained with Each Method with Full Employment

	Non-parametric microsimulation			Micro-accounting method		
Indicator	**Benchmark**	**Simulation results**	**Percentage variation**	**Benchmark**	**Simulation results**	**Percentage variation**
Poverty	42.1%	43.9%	4.3	42.1%	45.1%	7.1
Extreme poverty	29.6%	31.4%	5.7	30.5%	33.0%	8.2
Inequality (Gini index)	0.5808	0.5869	1.1	0.6057	0.6127	1.2

Table 3 presents results when we introduce unemployment in the labor market for unskilled and medium-skilled workers. Under this closure, results are more pronounced with the non-parametric microsimulation as there are now individuals that perceive no income as a consequence of the shock (as unemployment increases).

Table 3: Comparison of Results Obtained with Each Method with Unemployment

	Non-parametric microsimulation			Micro-accounting method		
Indicator	**Benchmark**	**Simulation results**	**Percentage variation**	**Benchmark**	**Simulation results**	**Percentage variation**
Poverty	42.1%	45.0%	6.9	42.1%	44.2%	4.8
Extreme poverty	29.6%	32.3%	9.2	30.5%	32.1%	5.3
Inequality (Gini index)	0.5808	0.5886	1.4	0.6057	0.6103	0.8

5. Concluding remarks

Micro-macro syntheses have become a powerful tool to capture the micro effects of macro policies and external shocks on income distribution and poverty. The range of techniques is wide and their implementation will depend on the objectives of the study and the availability of time and data, as well as the compatibility with the macro model applied, which is generally a general equilibrium model. In this guide, we present the different techniques and briefly describe their pros and cons. We also provide a specific example of two techniques: a non-parametric microsimulation model and a representative household model. We apply both techniques to analyze the impact of trade liberalization in Tanzania. We obtain similar poverty results by applying both methods. These results are due to the underlying CGE model assumptions: fixed employment level and perfectly mobile labor. When we introduce unemployment in the CGE model, we obtain more pronounced results under the non-parametric microsimulation model, as we account for unemployed individuals at the micro level.

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