Macro Models and Household Survey Data: Linkages for Poverty and Distributional Analysis

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Abstract

This paper focuses on approaches to linking macroeconomic models to household income data for poverty and distributional and analysis. Given that linkage methods can influence the resulting poverty and income distribution effects, understanding the benefits and costs of various linkages is important. Simulation exercises do not show fundamentally different results when comparing three approaches: a simple micro-accounting method, an extension of that method to account for changes in employment structure, and the Beta distribution approach. However, potential differences can be very large. We also highlight the extended micro-accounting method as a practical approach to linking macroeconomic models to household income data.

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1. Introduction

In recent years renewed efforts have been made (at the World Bank and elsewhere) to develop new policy tools aimed at better understanding the channels through which adjustment policies affect the poor and the possible trade-offs that poverty reduction strategies may entail regarding the sequencing of policy reforms.

One approach consists of using disaggregated computable general equilibrium (CGE) models that distinguish between several *representative household groups* (RHG), according to their education level (skilled and unskilled), their location (rural and urban), and their sector of employment. In these models, henceforth referred to as "Macro-RHG models", the distributional and poverty effects of macroeconomic shocks are generally based on the association between household-group-specific mean incomes and the state of poverty. For instance, if the mean income of workers in the rural tradable goods sector is below the poverty line, all workers in the sector are considered poor. Likewise, inequality indicators are based only on the distance between group-specific means. Therefore, within-group heterogeneity (dispersion around group means) is completely ignored, or in other words, it is assumed that within-group distributions are uniform.

However, a common observation is that the contribution of within-group income inequality to overall income inequality is much more important than that of between-group inequality, even if households are disaggregated in relatively small groups. For example, if Ivorian households are classified in ten groups according to activity sector and educational attainment of the household head, more than 80 percent of the variance of household incomes per capita is within groups. Likewise, a similar classification into ten groups for the Indonesian population leaves 74 percent of the total variance unexplained.[1] Because, by definition and construction, Macro-RHG models do not account for intra-group heterogeneity, they cannot provide much insight in the analysis of the impact of government policy or exogenous shocks on income distribution.

[1] These estimates are derived from computations by the authors, based on household surveys of the respective countries.

One approach to extend the use of such Macro-RHG models for poverty and income distribution analysis is to link the macroeconomic model with household survey data, thereby forming a framework with macro and micro components. The linkage methodology between the macroeconomic model and survey data clearly determines the channel(s) and extent to which macroeconomic shocks are transmitted to the micro component of the framework, which consequently affects the resultant changes in poverty and income distribution.

There are two broad categories of methodologies for linking macro models to household surveys. The first transmits the resultant changes in incomes, prices, and sometimes employment using either 'accounting methods' or parametrical methods to generate changes in the income distribution. These methods use only the minimum of the observed hetereogeneity in household surveys and do not postulate any behavior for households when transmitting the changes. In contrast, the second methodology transmits these changes explicitly via econometrically estimated behavioral equations to the household survey. Our focus in this paper is on the first category of methods.[2] Methods within this category have the advantage that they are rather easy to implement, which is especially important for developing countries whenever skills and resources are limited. However, it is important to understand more fully the benefits and costs of these various linkages within this methodology by comparing the results they produce. To our knowledge such systematic comparisons have never been made.

This paper addresses this gap in the literature by comparing three commonly used approaches that belong to the first category of linkage methodologies.[3] Knowing the benefits and costs of these different approaches are pertinent for enabling researchers and policymakers to choose between them. In addition, understanding the robustness of the simulated distributional effects is very important given that changes in poverty and

[2] For an example of the use of the second methodology, see Robilliard, Bourguignon and Robinson (2002).

[3] For a comparison of the second category of methodologies, see Cogneau and Robilliard (2004).

income distribution are the key indicators international donors and policymakers look to when deciding between different policy options.

Of the three approaches, note that the first two are micro-accounting methods and are non-parametrical in nature, while the third is purely parametrical. The first approach was initially proposed by Agénor, Izquierdo and Fofack (2003) and was used subsequently in the number of other studies. It assumes a stable within-household group distribution and employment structure. Shocks are introduced by applying changes in household-group-specific income and consumption to that of each household in the household income survey. The new poverty and distributional indicators are then computed on the basis of the "adjusted" post-shock household data. The second approach is to our knowledge new and extends the first by accounting for changes in the employment structure predicted by the macro component. This is achieved by modifying the weight given to each household group in the survey. The third approach uses estimated income distributions to measure distributional changes.[4] It imposes a fixed, parametrically estimated distribution of income within each household group and assumes that shocks shift the mean of these distributions without modifying their shape. Poverty indicators are then computed on the basis of these new distributions. We select one variant of this approach that uses the Beta distribution to compare with the micro-accounting methods.

To illustrate and compare these three approaches we use the Mini-IMMPA macroeconomic framework developed by Agénor (2003) and repeat a pair of experiments with each approach. The Mini-IMMPA CGE model is based on a four-good production structure combined with five categories of households, consisting of workers in the rural sector, the urban informal sector, the urban unskilled formal sector, the urban skilled formal sector, and the capitalists-rentiers. This framework focuses only on the "real" side of the economy and provides a very detailed treatment of the labor market, which is important for comparing the first and second approaches. We use a calibrated prototype version of the model for a "typical" middle-income developing country and link it to fictitious (but representative) household income and expenditure survey.

The remainder of the paper is organized as follows. Section 2 presents the three alternative approaches to micro-macro linkages that we intend to compare. Section 3 outlines the structure of Mini-IMMPA, the RHG framework that we use for our comparisons. Section 4 presents the simulation results of various policy-induced shocks on income distribution and poverty and uses them to compare the three approaches presented in Section 3. The last section summarizes our main results and suggests further extensions of our analysis.

2. Integrating Survey Data in Macro-RHG Models

In this section, we present three different approaches to linking Macro-RHG models with information from a Household Income Survey.[5] The first two approaches are so-called "micro-accounting" approaches. As for the third, the Macro-RHG model supplies the household module with group-specific changes in mean income. The household survey provides additional information on income dispersion in each group, which is assumed fixed across different simulations.

2.1 A Simple Micro-Accounting Method

With this method, the household survey data are classified into the household categories as distinguished by the macro model. Following a policy or exogenous shock, nominal growth rates in per capita consumption and disposable income for all household categories are obtained from the macro model. These household-group specific growth rates are then applied separately to the per capita disposable income and consumption

[4] This approach was pioneered by Adelman and Robinson (1978) and Dervis, de Melo and Robinson (1982). It has been used more recently by Decaluwé, Dumont and Savard (1999), and Decaluwé, Patry, Savard, and Thorbecke (1999). See also Agénor, Chen, and Grimm (2004).

[5] For instance, the Integrated Survey (IS) or Living Standard Measurement Survey (LSMS).

expenditure of each household in the survey, thereby providing the post-shock levels of nominal income and consumption. Initial poverty lines are updated using the price indexes generated by the macro model, to reflect changes in the price of the consumption basket and purchasing power of income for each group. Poverty and income distribution indicators are then calculated using the updated survey data and new poverty lines.[6] Figure 1 summarizes the procedure.[7]

[Figure 1 around here]

While appealing from a practical point of view, this approach has two main shortcomings. The first is that it does not fully account for heterogeneity among agents within groups. The application of group-specific, instead of household-specific, real growth rates of consumption or income assumes that the intra-group distribution of consumption and disposable income remains constant after a shock, which in reality may not be the case. The second shortcoming is that, given that changes in the employment structure are ignored, this approach only partially introduces the effects of the macroeconomic shock to the micro component. When the changes are transmitted to the household survey, it is thus assumed that each individual remains in his or her initial sector of activity. Put differently, labor market mobility is assumed to affect poverty and income distribution only through relative income changes.

2.2 An Extension with Reweighting Techniques

To account for changes in the employment structure at the micro-component of the framework, our second approach involves the combination of the micro-accounting method with reweighting techniques. This approach is to our knowledge new and original. Note that in the macro-economic model that we use later on, the employment

[6] See the Mathematical Appendix to this paper for detailed descriptions regarding the poverty and income distribution indicators used in this paper.

[7] Note that this approach to micro-macro linkage is “top-down” by construction, as there are no feedback effects from the household survey to the Macro-RHG model. More specifically, market equilibria are entirely simulated on the macro-side without accounting for any further heterogeneity in behavior within groups.

variable is constructed on the basis of three socio-economic variables: location (rural or urban), sector of employment (agriculture, informal, or formal), and educational attainment (skilled and unskilled). Hence, we distinguish five categories of employment: workers in the rural sector, the urban informal sector, the urban unskilled formal sector, the urban skilled formal sector, and the capitalists-rentiers. It is intuitively clear that large changes in the employment structure may have strong effects on poverty and income distribution.

In general, reweighting adjusts the socio-economic population structure to produce projections of the population over time (or before and after a shock). The underlying characteristics of the population are held constant, while the weights given to each set of characteristics in the sample are changed. For instance, if the macro-economic model predicts that the post-shock share of informal workers increases then reweighting would imply that a higher post-shock population weight should be assigned to informal workers in our sample. To reach overall consistency, one has to put some restrictions on the reweighting procedure. For instance, in our case we put as restriction that after the reweighting is done, the employment shares of each of the household groups of the population has to correspond exactly to that given by the macro-economic model after the shock is simulated. For the poverty assessment the reweighting approach involves then constructing the poverty or income distribution index for the population as being the weighted average of the household-group specific indices, where the weights are the respective period-specific employment shares of the household groups as projected by the macro-economic model. For example, the headcount index for the population after the shock is the reweighted average of the headcount indices of the individual household groups.[8] The procedure is summarized in Figure 2. In addition, note that while it is assumed in this approach that the intra-group distributions remain unchanged, the sum of the within-group inequality will change as the weights of the various groups change.

[Figure 2 around here]

[8] Refer to the mathematical appendix for details.

2.3 The Use of Distribution Functions

The third approach uses parametric distributions to describe the dispersion of income within each group. The parameters of these distributions are estimated using household survey data. Unlike the previous two approaches, once the parameters are estimated, the survey data are not used further to evaluate the distributional effects of shocks. Following a shock, the fitted distributions are only shifted according to the changes of the group-specific mean incomes, without modifying the shape (or other characteristics) of the distributions. The poverty indicators are also computed using the estimated shape parameters, without relying on the survey data. The overall distribution of income is generated empirically by summing the separate within-group distributions and is then used to generate overall measures of poverty and inequality. Given that the household survey data are discarded once the shape parameters are estimated, the distribution function approach assumes implicitly that intra-group inequality does not change following a shock, similar to the two previous approaches.

As in Decaluwé, Patry, Savard and Thorbecke (1999) and Decaluwé, Dumont and Savard (1999), we use Beta distribution functions to describe the within-group distributions.[9] Figure 3 summarizes the simulation procedure when using the Beta distribution method.[10] Initial experiments indicated that the estimation results were very sensitive to outliers. To increase the goodness of fit of our estimates, we eliminated for each household group the five highest and five lowest values of the distribution.[11] Table A1 in the Appendix compares the observed values for the poverty headcount and gap with the fitted values using both sets of estimated shape parameters, that is, with and without dropping the extreme values (as defined above).

[9] Given their high degree of flexibility, the assumption of Beta distributions may be a good choice in a real country case. Boccanfuso, Decaluwé and Savard (2002) compared six alternative functional forms to model within-group distributions and concluded that no single form is more appropriate in all cases or groups of households. However, especially when detailed disaggregation is required, they also advocated the use of rather flexible forms such as the Beta function, which allows, for instance, distributions to be very negatively skewed.

[10] Further details of this method can be found in the mathematical appendix.

[11] Of course there exist much more powerful and reliable methods to detect and eliminate outliers (see e.g. Deaton, 1997). These methods should be used in a real country application, when detailed information on socio-economic characteristics of the households is available.

[Figure 3 around here]

From Table A1, it can be seen that if we correct the data for outliers the fit is quite acceptable for the headcount index, at least for households in the rural sector and households in the informal urban sector. For instance for those households whose income comes predominantly from the urban informal sector, the observed poverty headcount is 43.35%. Using the parametrical approach, we estimate (or "fit") a poverty headcount of 51.59% if outliers are not eliminated. If outliers are eliminated, the estimated poverty headcount is 45.66% and therefore much closer to the "observed" value. However, for the other three groups, the deviations remain significant. One explanation for this outcome is that the population size is smaller for these groups, and thus the estimated shape parameters are less reliable. The poverty gap ratio is much more difficult to fit. Here the predicted indicators are more than 40 percent above the observed values. These results show the first limitation of the distribution approach, especially if sample sizes are small. Further implications will be discussed below.

3. The Macro-RHG Framework

Mini-IMMPA is a simplified version of the Integrated Macroeconomic Model for Poverty Analysis developed by Agénor, Izquierdo and Fofack (2003), and Agénor, Fernandes, Haddad, and Jensen (2003). The model is based on a four-good production structure (rural, urban informal, urban private formal, and urban public formal) combined with five categories of households. The model focuses only on the "real" side of the economy and hence its building blocks consist of production, employment, demand, external trade, sectoral and aggregate prices, income formation, consumption and savings, private investment, and the public sector. One of many strong points of the model include its detailed treatment of the labor market,[12] which is important for poverty

[12] Mini-IMMPA accounts for labor market features such as bilateral wage bargaining, free public education, employment subsidies, job security provisions and firing costs in the formal sector.

analysis, as incomes are strongly connected with the sector of employment in many developing countries. Households in Mini-IMMPA are defined according to their skills and their sector of employment. There is one rural household, comprising all workers employed in the rural sector. In the urban sector there are two types of unskilled households, those working in the informal sector and those employed in the formal sector (public and private). The fourth type of households consists of skilled workers employed in the formal urban economy (in both the private and public sectors). Finally, there are capitalists-rentiers whose income comes from firms' earnings in the urban private sector. The model accounts for the migration of workers from the rural sector to the urban (informal) sector, and the transformation of unskilled labor into skilled labor via a publicly provided education technology.

The household survey data used in the Mini-IMMPA framework is an artificial sample consisting of 5,000 observations, where each observation represents one household and the share of each household category corresponds exactly to that in the macro model.[13] Using a random number generator following a lognormal distribution, values for disposable income and consumption expenditure were drawn for each household.[14] For simplicity, poverty lines were assumed to remain constant in real terms up to the end of the simulation horizon.[15] Table 1 provides the initial values of the poverty and income distribution indices.[16]

[Insert Table 1 around here]

[13] See Table 1 for the initial employment shares.

[14] The initial values for average disposable income for each household group were set so as to equal that of the numerical solution of the macro model.

[15] The income poverty line for the rural sector was set such that the percentage of poor households in the rural sector is 50 percent. The poverty line in urban areas was assumed to be 15 percent higher. Rural and urban poverty lines for consumption expenditure were constructed in similar way.

[16] See Agénor (2003, 2004) for a more detailed presentation of the Mini-IMMPA framework.

4. Comparing Shocks with Alternative Linkages

To compare the performance of the three alternative approaches to model micro-macro linkages discussed earlier, the growth, employment and poverty effects of two types of labor market policies are examined in this section: a cut in the minimum wage and an increase in the employment subsidy on unskilled labor in the urban formal sector. Both experiments relate to critical policy issues in developing countries. As an indicator of living standards, we consider in what follows only disposable household income per capita.[17]

4.1 Reduction in the Minimum Wage

The simulation results associated with a permanent 7 percent reduction in the minimum wage are illustrated in Tables 2 and 3 for the first 10 periods after the shock. This time span is referred to below as the "adjustment period". Table 2 provides data on the labor market. Table 3 presents data on poverty and distributional indicators, all in absolute deviations from the baseline solution.[18] A more detailed presentation can be found in Agénor, Chen and Grimm (2004). We first comment on the general results of this simulation and then compare more specifically the effects on poverty and inequality, as measured by the three different methods.

[Insert Tables 2 and 3 around here]

Figure 4 illustrates selected general results of the simulation. The reduction in the minimum wage on impact results in an increase in the demand for unskilled labor in the private sector. The number of unemployed unskilled workers in the urban sector therefore falls, along with the unskilled unemployment rate. Hence, for unskilled

[17] In a real country application it may be worthwhile to test the sensitivity of the results to alternative equivalence scales.

[18] The experiment assumes that the government borrows domestically to finance its deficit, implying therefore an offsetting adjustment in private investment (at the initial level of foreign saving), in order to maintain the aggregate balance between savings and investment.

workers in that sector, both measures of poverty indicate an improvement in the longer run.[19] The fall in the minimum wage also leads to a drop in the expected urban unskilled wage[20], and consequently to a reduction in migration flows from rural to urban areas. This results in a relatively larger supply of rural workers, thus leading to a drop in nominal wages for rural workers. By the end of the adjustment period, both the proportion of poor households and the poverty gap in rural areas increases.

[Insert Figure 4 around here]

With the reduction in rural-urban migration flow, labor supply in the informal sector falls and informal sector wages increases throughout the adjustment period. Both measures of poverty for the informal sector therefore indicate an improvement in the longer run. Because the cut in the minimum wage reduces the relative cost of unskilled labor, demand for both skilled labor and physical capital falls, along with skilled wages and the rental price of capital. Hence, poverty for skilled workers tends to increase slightly in both the short and the long run. Similarly, the incidence of poverty for capitalists and rentiers increases toward the end of the adjustment period. Overall, poverty increases in rural areas and decreases in urban areas, resulting in a slight decrease in poverty at the economy-wide level. Changes in the income-based Gini coefficient indicate that income distribution is affected only modestly by a cut in the minimum wage; by contrast, the degree of inequality falls by a small amount in the long run.

We now examine the differences concerning changes in poverty and inequality as measured by the three approaches to micro-macro linkages presented in section 2. As can be seen from Table 3, using the simple micro-accounting method without reweighting, the decrease in poverty tends to be larger, compared to the approach that involves reweighting. Even though the absolute differences between the estimates are

[19] However, note that poverty increases on impact. There is therefore a potential short-run trade-off emerging between unemployment and poverty: although the reduction in the minimum wage lowers open unskilled unemployment in the formal sector, it also increases poverty for that category of households. See Agénor (2004) for a more detailed discussion of unemployment-poverty trade-offs.

[20] This is despite the increase in unskilled employment in the private sector in the first period, which raises the probability of finding a job.

relatively small, the discrepancies become significant when compared to the small total reduction in poverty predicted for the initial period.

Figure 5 traces the deviations from the baseline results obtained with the simple micro-accounting method as a ratio to those obtained with reweighting, for both the headcount and gap measures.[21] For both *urban households* and *all households* the decrease in poverty estimated by the non-reweighting approach is larger over the entire adjustment period. The difference amounts to up to 9 percent for *urban households* and nearly up to 20 percent for *all households*. The discrepancy between the estimates tends to decrease over the adjustment period for *urban households*, whereas that for *all households* tends to increase. The estimated decrease in inequality also tends to be larger if changes in the employment structure are not taken into account. Again, in absolute terms the difference is not large, but given the small change in inequality, the relative difference is significant.

[Insert Figure 5 around here]

Comparison of the estimated changes from the micro-accounting framework and the Beta distribution approach show that results from both approaches are consistent in terms of direction of changes in poverty headcount and gap measures. As with the micro-accounting approach, reweighting tends to produce small reductions in poverty. We also note that the Beta distribution approach tends to predict, with a few exceptions, changes in poverty of larger magnitude, compared to the micro-accounting approach.

Figure 6 shows the differences between the estimated changes from the Beta distribution approach relative to that of the micro-accounting approach. For workers in the rural sector, the discrepancy fluctuates between plus-minus 50 percent, but the actual numbers tend to be lower in the beginning and at the end of the adjustment period. For

[21] In Figure 5, positive (negative) values reflect the fact that both approaches predict a change in poverty in the same (opposite) direction. A value greater than 1 implies that the predicted value from the approach without reweighting is larger than that with reweighting. Similarly, positive values smaller than 1

urban informal workers, decreases in the poverty gap using the Beta distribution are systematically 25 to 30 percent larger, whereas decreases in the headcount measure are around 10 percent smaller than those obtained with the micro-accounting approach. For urban formal unskilled workers, changes predicted by the Beta distribution are larger by 100 to 250 percent for the headcount measure and nearly 100 percent for the poverty gap measure. For skilled workers in the urban sector, the deviations for the poverty gap measure are up to 6 times the change indicated by the micro-accounting with reweighting method, but are in general small for the headcount measure. The fact that the beta distribution approach rather overestimates poverty is not surprising given that it tends to overestimate poverty already in the base year (see Table A1). This bias then also shows up when the beta distribution is used to forecast poverty changes.

[Insert Figure 6 around here]

4.2 Increase in Employment Subsidy

The simulation results associated with a permanent, doubling of the nominal employment subsidy on unskilled labor in the private formal sector (an increase in the subsidy rate from 5 to 10 percent of the minimum wage) are illustrated in Tables 4 and 5 for the first 10 periods after the shock. This subsidy is assumed to be paid on a per worker basis.

[Insert Tables 4 and 5 around here]

Similar to the effect of a reduction in the minimum wage, an increase in the employment subsidy reduces the effective cost of unskilled labor (Figure 7). Demand and thus formal unskilled employment expands, and the unskilled unemployment rate falls, which results in lower values in the corresponding poverty headcount and gap indices.

imply smaller changes from the approach without reweighting, and values equal to 1 imply that both approaches predict changes in poverty that are of the same magnitude.

[Insert Figure 7 around here]

The increase in formal unskilled employment raises the inflow of workers from the informal to the formal sector, leading to a corresponding increase in the informal wage. As a result, poverty in the informal sector decreases throughout the adjustment period. The reduction in the “effective” cost of unskilled labor leads firms in the private formal urban sector to substitute away from skilled labor and physical capital, leading to a reduction in skilled wages and capital rental prices. Consequently, poverty increases for both of these household groups. Rural-urban migration flows also increases, which in turn decreases labor supply in the rural sector and rural wages therefore tend to increase. Rural poverty consequently decreases, at least in the short run. As with the cut in the minimum wage, inequality in the distribution of disposable income decreases.

In terms of difference in results due to the alternative linkage methods, we see from Table 5 that the simulated changes in poverty are larger with the simple micro-accounting method without reweighting, as compared to those obtained with reweighting. Again, because changes in the employment structure following the shock are small, the absolute differences are also small, but relatively significant when compared to the decrease in poverty. Figure 8 illustrates the absolute deviations from the baseline measured by the simple micro-accounting method without reweighting relative to that with reweighting. For both poverty indicators, and for *urban households* and *all households*, changes in poverty with the micro accounting approach are larger in the short run (approximately 5 percent) and smaller in the long run (also by approximately 5 percent). In addition, the method involving no reweighting produces smaller decreases in inequality, as compared to that with reweighting. The difference between the two methods are again very small in absolute terms, but large in relative terms.

[Insert Figure 8 around here]

Figure 9 illustrates the comparison of the results from the Beta distribution approach and the micro-accounting framework. The relative changes in poverty were typically equivalent for both poverty measures. For workers in the rural sector, and relative to the micro-accounting approach, the Beta distribution approach produces changes in poverty that are slightly larger at the beginning of the adjustment period, changes that are large and of the opposite sign in the middle of the adjustment period, and nearly identical changes towards the end of the adjustment period.

[Insert Figure 9 around here]

For the urban informal sector, the Beta distribution approach simulated changes in poverty that were consistently larger; for the poverty headcount index in the long run it was larger by more than 30 percent, and for the poverty gap by 20 to 30 percent throughout the adjustment period. For unskilled workers in the urban formal sector, changes in the headcount poverty measure simulated by the Beta distribution are very volatile, ranging from negative 1000 to positive 300 percent of those obtained with the micro-accounting methods. The poverty gap measure is somewhat more stable, ranging from negative 200 to positive 100 percent. For skilled workers in the urban formal sector, changes in both poverty indicators are more than 2 to 10 times higher, but the deviations decrease over time. For capitalists and rentiers, the Beta distribution approach indicates no change in poverty, with either measure of poverty, whereas the reweighting approach indicates that poverty increased.

In summary, the simulation of both experiments using the three alternative linkage approaches led to qualitatively similar results: an increase in rural poverty, a decrease in urban poverty, a decrease in economy-wide poverty measures and an improvement in the economy-wide income distribution. However, a comparison of changes in poverty and income distribution measures at a disaggregated level shows that large differences in outcomes (both quantitative and qualitative) also exist.

5. Conclusion

This paper focused on the various approaches to linking macroeconomic models with representative households to micro household income data. Such linkages between models and survey data form frameworks that are used to evaluate the distributional and poverty effects of policy and other exogenous shocks. We compare three linkage approaches by simulating two exogenous policy shocks with the Mini-IMMPA framework developed by Agénor (2003), using each approach in turn. The selected shocks are a cut in the minimum wage and an increase in employment subsidies for unskilled labor in the formal urban sector. The resulting effects on poverty and income distributions were then evaluated and compared.

We found that the distributional and poverty effects indicated by the three approaches are generally similar, especially at the economy-wide level. With all three approaches, both experiments lead to an increase in rural poverty, a decrease in urban poverty, a decrease in economy-wide poverty and an improvement in the economy-wide distribution of income. However, closer comparisons between the simulation results using the micro-accounting approach with and without reweighting reveal that the latter produced larger decreases in poverty for aggregated household groups in both experiments. In addition, we observed some substantial differences in the simulated changes in poverty at the sectoral level, both in terms of magnitude and the direction of change, between the micro-accounting and Beta distribution approaches.

From both a conceptual and practical point of view, it is tempting to view the micro-accounting method combined with reweighting for changes in the employment structure as constituting the most appealing method among the three, despite the fact that it has its own shortcomings. The reason is that the simple micro-accounting method ignores a potentially crucial feature of the economy’s response to shocks (namely, changes in the composition of employment), whereas the distribution approach relies on estimated instead of real income distributions, and depends therefore on the quality of the corresponding estimates of the shape parameters.

In the past, a key advantage of the distribution approach was that it enabled simulations to be conducted without the direct use of the actual household survey data (beyond the estimation of distributional parameters), thereby making simulations less computationally intensive. However, given today's computing power and statistical software, working directly with actual survey data does not present much of a constraint, except perhaps for very large household surveys (which are not yet common in developing countries). Hence, there is usually little need to use the distribution approach and discard much valuable information contained in household survey data. However, advocates of this approach also argue that if the sample of households is small, the use of the estimated distribution ensures smoothness, even if the observed one is not. The smoothing avoids the possibility that small shifts in the income distribution would lead to huge changes in the poverty measure, or conversely, that big shifts would lead to very small changes in the poverty measure. The problem with this argument is that the estimated distribution parameters are not very reliable if they are estimated over a small sample of households.[22] Therefore the parametric approach runs the risk of producing biased results, which may have been an important factor for the significant observed differences in the simulated changes in poverty.

The potential errors associated with the use of the simple micro-accounting approach without reweighting or the distribution method are obviously more important if policies with strong effects on the employment structure and the group-specific income levels are analyzed. For instance, simulations with our model show that if the minimum wage were reduced by 50 percent, the employment structure would change drastically--with the share of rural workers decreasing by 50 percent, the share of informal workers increasing by 25 percent and the share of formal unskilled workers doubling. Poverty indicators calculated by either method would differ by more than 10 percentage points, depending on whether these changes in employment structure are taken into account or not. Although a shock of this magnitude may be viewed as implausibly large, this

[22] This issue is illustrated in Table A1. For instance, compare the observed and fitted poverty measures for the group of skilled workers in the formal urban sector and of capitalists-rentiers.

argument is quite general. Indeed, many of the policies that form part of poverty reduction strategies (such as changes in the composition of public investment) are likely to generate substantial variations in the composition of employment in the long run. Even in our own experiments, changes in the employment structure would be a lot bigger than those we obtained, if migration flows were assumed to respond more rapidly and significantly to changes in relative wages. One can rightly conclude, therefore, that failure to account for such changes in employment structure can lead to severely biased simulation results. At the same time, whether this bias is greater or smaller than other difficulties typically associated with the use of macroeconomic models for policy analysis (such as parameter uncertainty) remains open to debate.

The micro-accounting framework with employment reweighting can be extended to account for changes in other dimensions of the population structure, such as age structure, household size, or gender—all potentially important considerations when conducting dynamic analyses. However, this framework also has its shortcomings. The most obvious one is the assumption of unchanged within-household group distributions. One possible remedy to account for individual and household heterogeneity is to allow the intra-group distributions to vary explicitly. This would entail the use of a micro-simulation model that accounts for labor supply decisions and earnings at the level of the household, or even, the individual. This methodology differs from the reweighting approach in that individuals would actually be simulated to shift from one sector to another using econometrically estimated behavioral functions, instead of merely changing the weights of household groups. The downside of micro-simulation approach is that it requires the use of a microeconomic model of income generation, and therefore relatively powerful statistical software for econometric estimation and simulation. In addition, good quality detailed data are also necessary, and this increases the difficulty of proper implementation. In contrast, the micro-accounting framework combined with reweighting for changes in the employment structure preserves a high degree of user-friendliness, which may help its eventual adoption by researchers and policy advisers in developing countries whenever skills and resources are scarce.

Mathematical Appendix

Measurement of Poverty

To measure poverty we use the Foster, Greer and Thorbecke's (FGT) poverty measure P_α (see Foster, Greer and Thorbecke (1984)):

$$P_{\alpha t} = \frac{1}{N} \sum_{y_{it}=0}^{z_t} \left(\frac{z_t - y_{it}}{z_t} \right)^{\alpha} ,$$

where α is a poverty-aversion parameter, N the total number of households in the survey, y_{it} household i's income or consumption in period t, and z_t the poverty line in period t. When α equals zero, the measure yields the headcount ratio, that is, the percentage of poor households. When α equals one, the measure yields the poverty gap index, that is, the average distance between income and the poverty line (where for non-poor households this distance is set to zero) as a fraction of the poverty line. These measures can be calculated for each household category j, as well as for the total population.

Measurements of Inequality

To measure inequality, we use the Gini coefficient and the Theil index. The Gini coefficient is given by:

$$G_t = 1 + \frac{1}{N} - \frac{2}{\bar{y}_t N^2} \sum_{i=0}^{N} (N - i + 1) y_{it} ,$$

where households are ranked in ascending order of y_{it} and $\bar{y}$ is the mean household income or consumption in period t. The Theil index is given by:

$$T_t = \sum_{i=1}^{N} \frac{1}{N} \frac{y_{it}}{\bar{y}_t} \ln\left(\frac{y_{it}}{\bar{y}_t} \right).$$

Reweighting Approach

Under the reweighting procedure, we calculate the household group-specific FGT poverty measures as before, but we now account for changes in the employment structure with respect to the initial period. The FGT poverty measures then become:

$$P_{\alpha t} = \frac{\sum_j P_{\alpha jt} w_{jt}}{\sum_j w_{jt}}$$

where the index j stands for the different household categories and w_{jt} for their respective share in the total population in period t. In the micro-accounting method presented earlier, the implicit assumption was that the coefficients w_{jt} remain constant over time.

Likewise, we can calculate the inequality measures by weighing each household with its group and period-specific weight f_{jt}, where $f_{jt}=w_{jt}/N_j$ with w_{jt} is the share of group j in the population at period t and N_j the size of group j in the initial period. In period $t=0$, f_{j0} is thus equal to $1/N$ for each household.

The Beta Distribution Method

The Beta density distribution is a continuous function taking values between 0 and 1 and has as formula:

$$I(x,\beta_1,\beta_2)=\frac{1}{B(\beta_1,\beta_2)}x^{\beta_1-1}(1-x)^{\beta_2-1},$$

where $B(\beta_1,\beta_2)$ is the beta function. x stands for the income variable normalized to values between 0 and 1. The parameters β_1 *and* β_2 can be estimated either by their moment estimators or by Maximum Likelihood Techniques.

Relying on the Beta density distribution, the FGT poverty measures computed for group j become:

$$P_{\alpha jt} = \int_0^{z'_{tj}} \left(\frac{z'_{tj} - x}{z'_{tj}} \right)^{\alpha} I(x, \hat{\beta}_{1j} \hat{\beta}_{2j}) dx$$

where z'_{tj} is the group and period-specific normalized poverty line. To calculate the poverty measures for the urban or the total population at t, we can either weigh the group-specific poverty measures by their initial population shares, w_{j0}, or by their population shares at t, w_{jt}.

Given that the household survey data are discarded once the shape parameters are estimated, and given that the distribution function approach assumes implicitly that intra-group inequality does not change following a shock, we limit the measurement of inequality to between-group inequality when using the Beta distribution approach. The Theil index allows an exact decomposition of total inequality between within- and between-group inequality. Between-group inequality, T_{Bt}, can be calculated as:

$$T_{Bt} = \sum s_{jt} \ln\left(\frac{\bar{y}_{jt}}{\bar{y}t} \right).$$

Therefore between-group inequality depends only on s_{jt}, the share of total income held by group j, $\bar{y}_{jt}$ the mean income in group j, and $\bar{y}_t$, the overall mean of income. We do not compute the Gini coefficient because it is not decomposable.

Assessment of the fit of the Beta Distribution Method

[Insert Table A1 here]

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Figure 1
Simple Micro-accounting Method

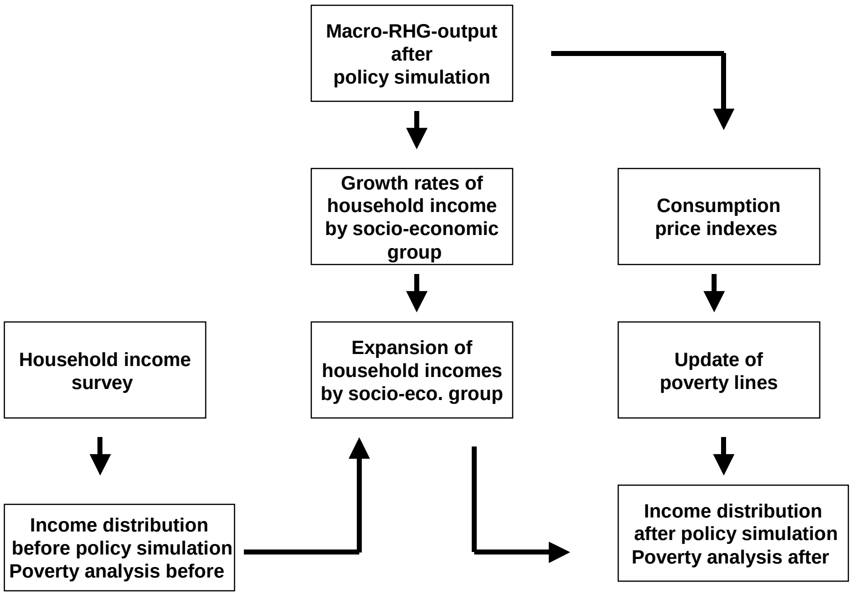

Figure 2
Reweighting Method

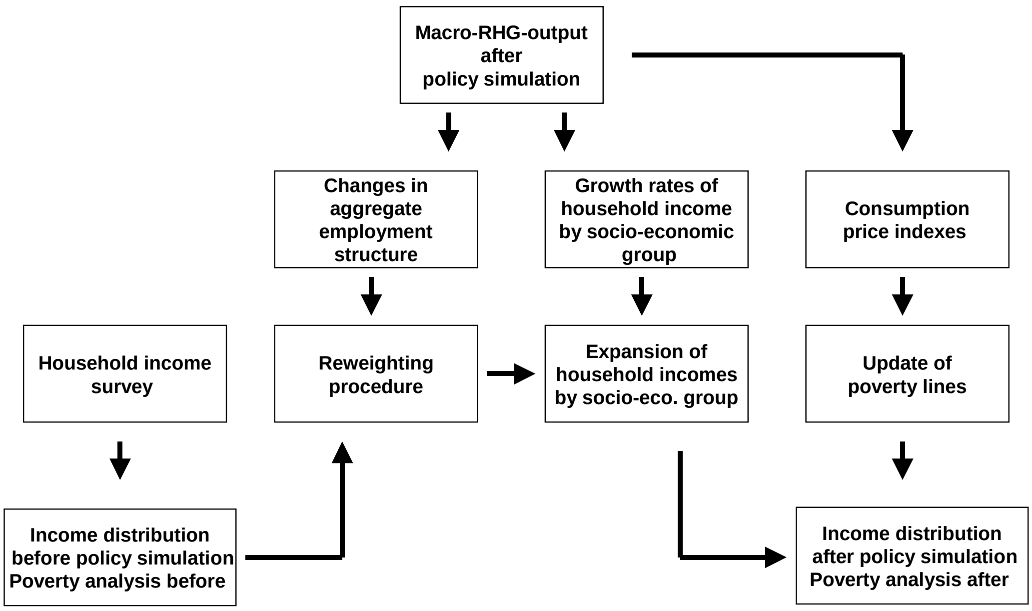

Figure 3
Beta Distribution Method

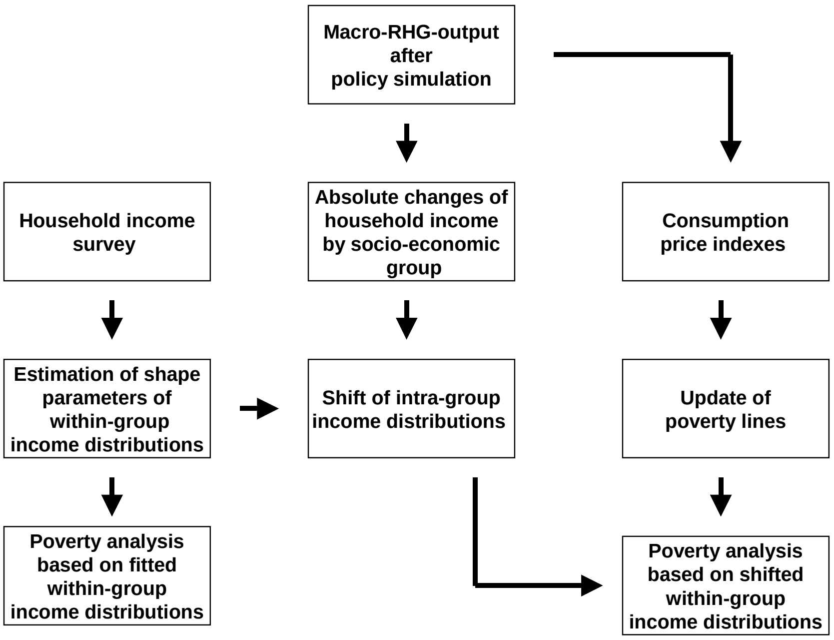

Figure 4
7% Cut in Unskilled Labor Minimum Wage

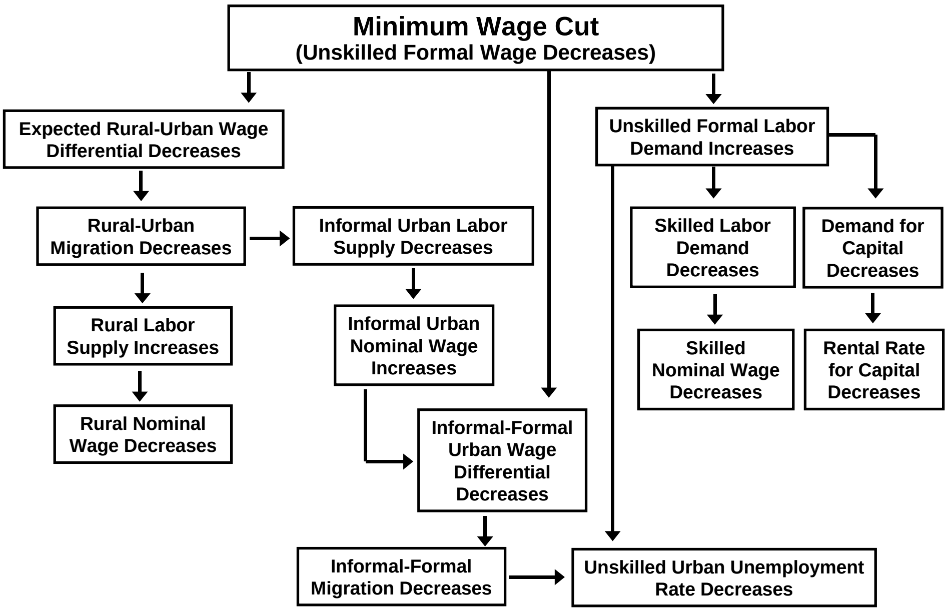

Figure 5
Relative Changes in Poverty
Simple Micro-Accounting Method, Without and With Reweighting
(No reweighting to reweighting ratio of absolute deviations from baseline)
Simulation: 7 Percent Cut in Unskilled Labor Minimum Wage

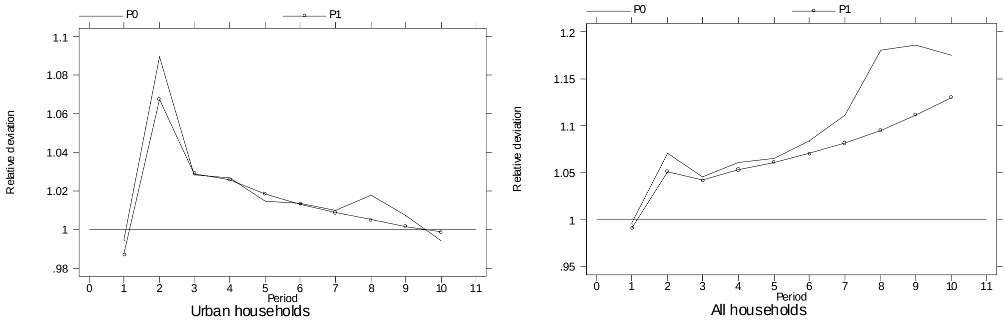

Figure 6
Relative Changes in Poverty
Beta Distribution Method and Micro-Accounting Method
(Beta distribution to Micro-Accounting ratio of absolute deviations from baseline)
Simulation: 7 Percent Cut in Unskilled Labor Minimum Wage

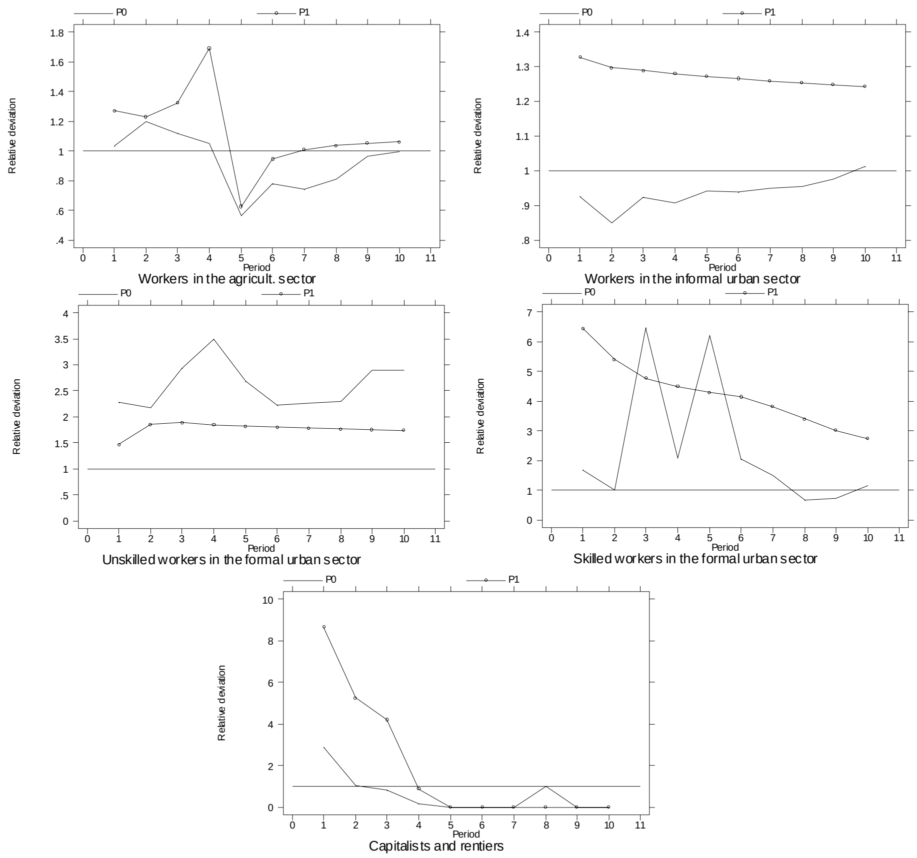

Figure 7
100% Increase in Unskilled Labor Employment Subsidy

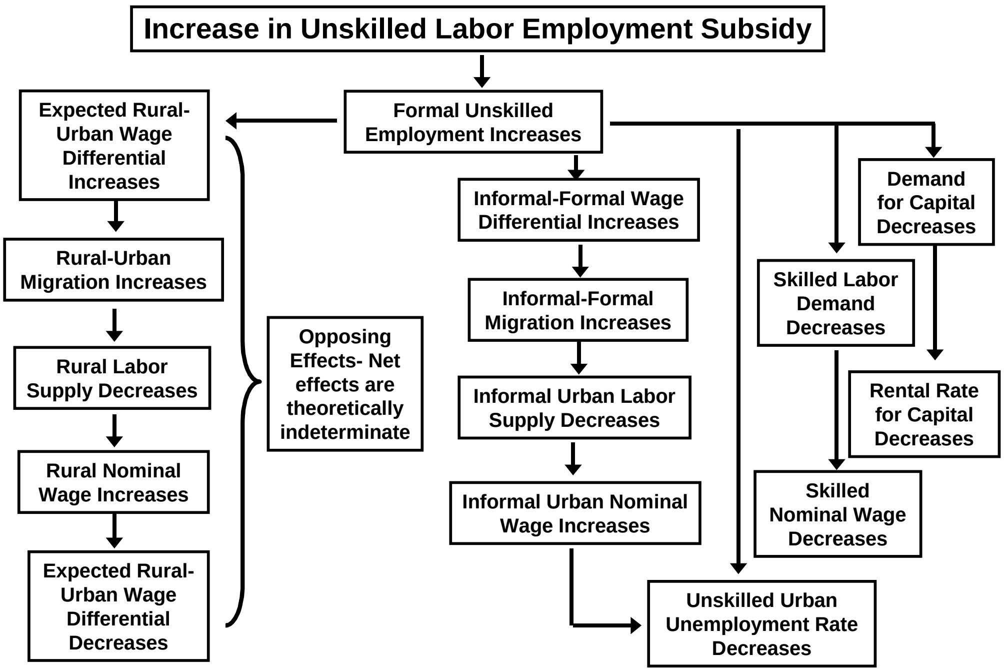

Figure 8
Relative Changes in Poverty
Simple Micro-Accounting Method, Without and With Reweighting
(No reweighting to reweighting ratio of absolute deviations from baseline)
Simulation: 100 Percent Increase in Employment Subsidy on Unskilled Labor

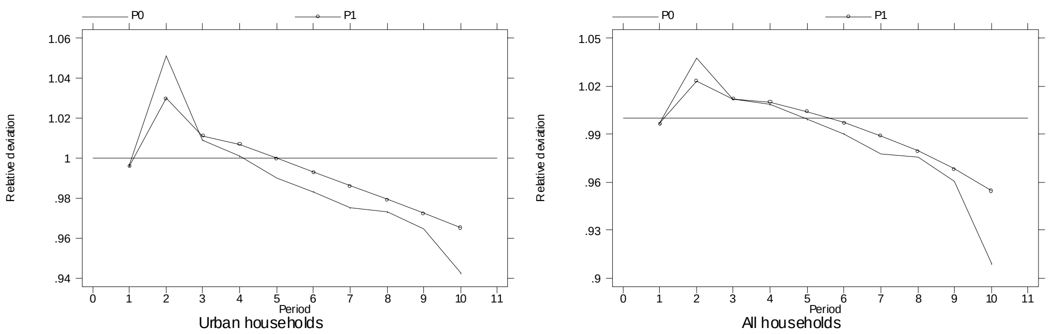

Figure 9
Relative Changes in Poverty
Beta Distribution Method and Micro-Accounting Method
(Beta distribution to Micro-Accounting ratio of absolute deviations from baseline, in percent)

Simulation: 100 Percent Increase in Employment Subsidy on Unskilled Labor

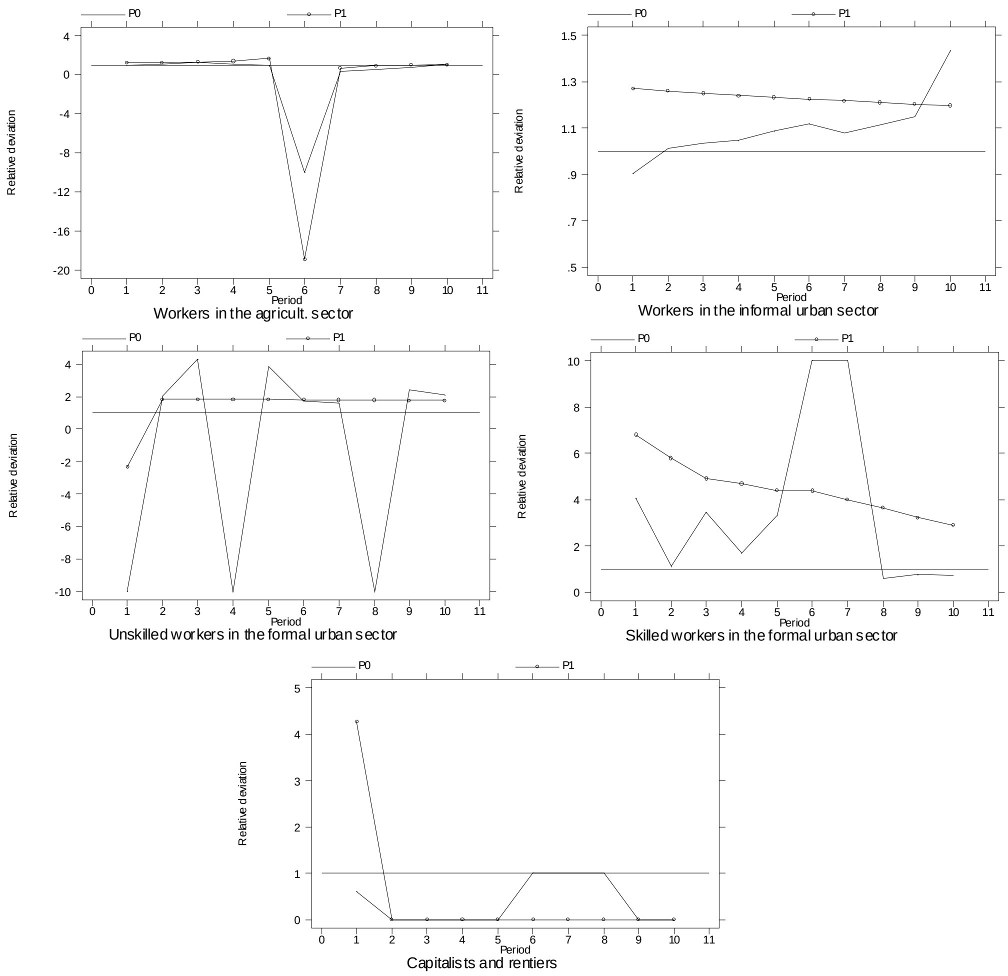

Table 1
Poverty and Income Distribution Indices - Initial Values

Household Groups	Household Group Share of Total Workers	Poverty Headcount Index	Poverty Gap Index	Gini Index
Rural	**28.1**	**50.0**	**50.1**	**45.2**
Urban Informal	**45.3**	**43.4**	**46.4**	**44.2**
Urban Formal Unskilled	**13.7**	**32.2**	**37.7**	**42.9**
Urban Formal Skilled	**9.9**	**4.4**	**8.3**	**38.5**
Capitalists-Rentiers	**3.0**	**3.3**	**2.0**	**38.5**
Economy	**100.0**	**38.6**	**15.6**	**49.1**

Table 2
Mini-IMMPA: Simulation Results for the Labor Market
7 Percent Cut in Unskilled Labor Minimum Wage
(Percentage deviations from baseline, unless otherwise indicated)

	Periods									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Nominal wages										
Agricultural sector	3.7	3.9	2.3	1.3	0.3	-0.6	-1.4	-2.2	-2.9	-3.5
Informal sector	5.4	3.1	3.9	4.0	4.2	4.3	4.4	4.5	4.6	4.7
Private formal sector										
Unskilled	-7.0	-7.0	-7.0	-7.0	-7.0	-7.0	-7.0	-7.0	-7.0	-7.0
Skilled	-5.2	-3.8	-4.3	-4.3	-4.4	-4.5	-4.6	-4.7	-4.8	-4.8
Public sector										
Unskilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Skilled	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Employment										
Agricultural sector	0.0	0.3	0.6	0.8	1.0	1.2	1.4	1.6	1.7	1.8
Informal sector	0.0	0.9	0.5	0.3	0.2	0.0	-0.1	-0.2	-0.3	-0.4
Private formal sector										
Unskilled	3.4	7.6	7.0	7.5	7.8	8.1	8.4	8.8	9.1	9.4
Skilled	-0.5	-0.3	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4
Public sector										
Unskilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Skilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Labor supply (urban formal sector)										
Unskilled	0.0	-3.6	-2.9	-3.0	-3.0	-2.9	-2.8	-2.7	-2.5	-2.4
Skilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Unemployment rate (urban formal sector) [1]										
Unskilled	-2.2	-8.6	-7.4	-7.9	-8.0	-8.2	-8.3	-8.4	-8.4	-8.5
Skilled	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Real wage differentials [1]										
Expected urban-rural (% of rural wage)	0.0	-12.7	-14.7	-12.5	-11.3	-10.0	-8.9	-7.9	-6.9	-6.0
Expected formal-informal (% of informal wage)	0.0	-9.5	2.1	-0.5	0.2	0.2	0.3	0.3	0.4	0.4
Migration [1]										
Rural-urban (% of urban labor supply)	0.0	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	0.0
Formal-informal (% of formal urban labor supply)	0.0	-3.6	0.8	-0.2	0.1	0.1	0.1	0.1	0.1	0.2

[1] Absolute deviations from baseline.

Table 3
Mini-IMMPA: Price, Poverty and Distributional Indicators
7 Percent Cut in Unskilled Labor Minimum Wage
(In absolute deviations from baseline, unless otherwise indicated)

	Periods									
	1	2	3	4	5	6	7	8	9	10
Household Shares										
Rural households	0.00	0.07	0.15	0.22	0.29	0.34	0.39	0.44	0.47	0.51
Urban households	0.00	-0.07	-0.15	-0.22	-0.29	-0.34	-0.39	-0.44	-0.47	-0.51
Informal	0.00	0.39	0.21	0.16	0.08	0.01	-0.05	-0.11	-0.17	-0.22
Formal unskilled	0.00	-0.47	-0.36	-0.38	-0.37	-0.36	-0.34	-0.32	-0.30	-0.28
Formal skilled	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Capitalists and rentiers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Poverty Line [1]										
Rural	1.31	1.09	0.94	0.79	0.65	0.52	0.40	0.28	0.18	0.08
Urban	0.75	0.55	0.55	0.51	0.48	0.45	0.42	0.39	0.37	0.34
Micro-accounting approach with and without reweighting										
Poverty Headcount										
Rural households	-1.14	-1.14	-0.64	-0.28	0.21	0.64	1.14	1.42	1.49	1.71
Urban households (without reweighting)	-1.34	-0.92	-1.17	-1.17	-1.28	-1.34	-1.34	-1.25	-1.22	-1.28
Urban households (with reweighting)	-1.34	-0.84	-1.14	-1.14	-1.26	-1.32	-1.32	-1.23	-1.22	-1.29
Informal	-2.61	-1.55	-1.86	-1.94	-1.99	-2.08	-2.12	-2.17	-2.17	-2.12
Formal unskilled	0.58	-0.88	-0.44	-0.44	-0.58	-0.73	-0.73	-0.73	-0.58	-0.58
Formal skilled	1.01	1.21	0.20	0.60	0.20	0.60	0.81	1.81	1.61	1.01
Capitalists and rentiers	1.33	1.33	1.33	1.33	1.33	0.67	0.67	0.00	0.67	0.67
Economy (without reweighting)	-1.28	-0.98	-1.02	-0.92	-0.86	-0.78	-0.64	-0.50	-0.46	-0.44
Economy (with reweighting)	-1.29	-0.92	-0.98	-0.87	-0.81	-0.72	-0.58	-0.42	-0.39	-0.37
Poverty Gap										
Rural households	-0.60	-0.71	-0.35	-0.11	0.12	0.34	0.54	0.72	0.88	1.03
Urban households (without reweighting)	-0.59	-0.50	-0.58	-0.62	-0.66	-0.69	-0.72	-0.74	-0.75	-0.77
Urban households (with reweighting)	-0.60	-0.47	-0.57	-0.60	-0.65	-0.68	-0.71	-0.73	-0.75	-0.77
Informal	-1.15	-0.64	-0.84	-0.87	-0.93	-0.97	-1.01	-1.05	-1.07	-1.09
Formal unskilled	0.54	-0.61	-0.41	-0.49	-0.51	-0.54	-0.55	-0.57	-0.58	-0.58
Formal skilled	0.14	0.12	0.15	0.15	0.16	0.16	0.18	0.19	0.22	0.24
Capitalists and rentiers	0.23	0.14	0.14	0.11	0.10	0.08	0.07	0.06	0.05	0.04
Economy (without reweighting)	-0.59	-0.56	-0.52	-0.48	-0.44	-0.40	-0.36	-0.33	-0.29	-0.26
Economy (with reweighting)	-0.60	-0.53	-0.50	-0.45	-0.41	-0.37	-0.34	-0.30	-0.26	-0.23
Overall Inequality [2]										
Gini-coefficient (without reweighting)	-0.0074	-0.0053	-0.0052	-0.0046	-0.0041	-0.0036	-0.0031	-0.0026	-0.0022	-0.0018
Gini-coefficient (with reweighting)	-0.0075	-0.0053	-0.0051	-0.0045	-0.0040	-0.0035	-0.0031	-0.0026	-0.0022	-0.0018
Theil-index (without reweighting)	-0.0153	-0.0116	-0.0111	-0.0099	-0.0089	-0.0079	-0.0069	-0.0059	-0.0050	-0.0041
Theil-index (with reweighting)	-0.0155	-0.0113	-0.0109	-0.0097	-0.0087	-0.0076	-0.0066	-0.0057	-0.0048	-0.0039
Beta-distribution approach with and without reweighting										
Poverty Headcount										
Rural households	-1.18	-1.36	-0.72	-0.30	0.12	0.50	0.84	1.16	1.44	1.70
Urban households (without reweighting)	-0.87	-0.97	-1.10	-1.22	-1.30	-1.37	-1.42	-1.46	-1.49	-1.51
Urban households (with reweighting)	-0.88	-0.88	-1.05	-1.17	-1.25	-1.32	-1.37	-1.42	-1.45	-1.48
Informal	-2.41	-1.31	-1.71	-1.77	-1.87	-1.95	-2.02	-2.07	-2.11	-2.15
Formal unskilled	1.33	-1.91	-1.29	-1.53	-1.57	-1.62	-1.66	-1.68	-1.69	-1.69
Formal skilled	1.70	1.22	1.30	1.27	1.25	1.24	1.22	1.20	1.19	1.17
Capitalists and rentiers	3.82	1.37	1.09	0.19	0.00	0.00	0.00	0.00	0.00	0.00
Economy (without reweighting)	-0.96	-1.08	-0.99	-0.96	-0.90	-0.84	-0.78	-0.72	-0.66	-0.61
Economy (with reweighting)	-0.96	-1.01	-0.94	-0.90	-0.84	-0.78	-0.72	-0.66	-0.60	-0.54
Poverty Gap										
Rural households	-0.76	-0.87	-0.46	-0.19	0.08	0.32	0.54	0.75	0.93	1.09
Urban households (without reweighting)	-0.60	-0.62	-0.71	-0.78	-0.83	-0.87	-0.90	-0.92	-0.94	-0.96
Urban households (with reweighting)	-0.61	-0.57	-0.68	-0.74	-0.80	-0.84	-0.87	-0.90	-0.92	-0.94
Informal	-1.52	-0.83	-1.08	-1.12	-1.18	-1.23	-1.28	-1.31	-1.34	-1.36
Formal unskilled	0.79	-1.13	-0.77	-0.91	-0.93	-0.97	-0.99	-1.00	-1.01	-1.01
Formal skilled	0.91	0.66	0.71	0.69	0.68	0.68	0.67	0.66	0.66	0.65
Capitalists and rentiers	1.99	0.71	0.57	0.10	0.00	0.00	0.00	0.00	0.00	0.00
Economy (without reweighting)	-0.64	-0.69	-0.64	-0.61	-0.57	-0.53	-0.49	-0.45	-0.42	-0.38
Economy (with reweighting)	-0.65	-0.65	-0.61	-0.58	-0.54	-0.49	-0.45	-0.41	-0.38	-0.34
Between-group Inequality										
Theil-index (without reweighting)	-0.0173	-0.0127	-0.0124	-0.0111	-0.0100	-0.0089	-0.0078	-0.0068	-0.0058	-0.0048
Theil-index (with reweighting)	-0.0174	-0.0127	-0.0124	-0.0110	-0.0099	-0.0088	-0.0078	-0.0068	-0.0058	-0.0048

[1] Percentage deviations from baseline. [2] Gini Coefficients and Theil Indices measure between-group inequality.

Table 4
Mini-IMMPA: Simulation Results for the Labor Market
Doubling (from 5 to 10 percent of the min. wage) in Employment Subsidy on Unskilled Labor
(Percentage deviations from baseline, unless otherwise indicated)

	Periods									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Nominal wages										
Agricultural sector	1.6	1.6	1.1	0.8	0.5	0.3	0.1	-0.1	-0.2	-0.4
Informal sector	2.5	1.8	1.9	1.8	1.7	1.7	1.6	1.5	1.5	1.4
Private formal sector										
Unskilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Skilled	-2.5	-2.1	-2.3	-2.3	-2.4	-2.4	-2.5	-2.5	-2.5	-2.5
Public sector										
Unskilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Skilled	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Employment										
Agricultural sector	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Informal sector	0.0	0.2	0.1	0.0	-0.1	-0.1	-0.2	-0.2	-0.3	-0.3
Private formal sector										
Unskilled	0.5	1.9	1.9	2.2	2.4	2.7	2.9	3.1	3.3	3.5
Skilled	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2
Public sector										
Unskilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Skilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Labor supply (urban formal sector)										
Unskilled	0.0	-0.8	-0.3	-0.1	0.1	0.3	0.5	0.7	1.0	1.2
Skilled	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Unemployment rate (urban formal sector) [1]										
Unskilled	-0.4	-2.0	-1.5	-1.6	-1.5	-1.5	-1.4	-1.3	-1.3	-1.2
Skilled	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Real wage differentials [1]										
Expected urban-rural (% of rural wage)	0.0	-1.4	-1.6	-1.0	-0.6	-0.3	0.0	0.3	0.5	0.7
Expected formal-informal (% of informal wage)	0.0	-2.1	1.2	0.5	0.6	0.6	0.6	0.6	0.6	0.5
Migration [1]										
Rural-urban (% of urban labor supply)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Formal-informal (% of formal urban labor supply)	0.0	-0.8	0.5	0.2	0.2	0.2	0.2	0.2	0.2	0.2

[1] Absolute deviations from baseline.

Table 5
Mini-IMMPA: Price, Poverty and Distributional Indicators
Doubling (from 5 to 10 percent of the min. wage) in Employment Subsidy on Unskilled Labor
(In absolute deviations from baseline, unless otherwise indicated)

	Periods									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Household Shares										
Rural households	0.00	0.01	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.02
Urban households	0.00	-0.01	-0.02	-0.02	-0.03	-0.03	-0.03	-0.02	-0.02	-0.02
Informal	0.00	0.09	0.02	0.00	-0.04	-0.06	-0.09	-0.11	-0.13	-0.15
Formal unskilled	0.00	-0.10	-0.04	-0.02	0.01	0.04	0.06	0.09	0.11	0.13
Formal skilled	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Capitalists and rentiers	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Poverty and Distributional Indicators (Income-based)										
Poverty Line [1]										
Rural	0.59	0.50	0.44	0.38	0.32	0.27	0.22	0.18	0.15	0.12
Urban	0.34	0.27	0.26	0.23	0.21	0.19	0.17	0.15	0.14	0.12
Micro-accounting approach with and without reweighting										
Poverty Headcount										
Rural households	-0.50	-0.50	-0.28	-0.21	-0.14	0.00	0.14	0.21	0.21	0.21
Urban households (without reweighting)	-0.70	-0.45	-0.47	-0.39	-0.42	-0.47	-0.47	-0.25	-0.25	-0.17
Urban households (with reweighting)	-0.70	-0.42	-0.47	-0.39	-0.42	-0.48	-0.49	-0.26	-0.26	-0.18
Informal	-1.24	-0.75	-0.80	-0.75	-0.71	-0.66	-0.66	-0.62	-0.57	-0.44
Formal unskilled	0.00	-0.44	-0.15	0.00	-0.15	-0.29	-0.29	0.00	-0.15	-0.15
Formal skilled	0.20	0.60	0.20	0.40	0.20	0.00	0.00	1.01	0.81	0.81
Capitalists and rentiers	1.33	0.67	0.67	0.67	0.67	0.00	0.00	0.00	0.67	0.67
Economy (without reweighting)	-0.64	-0.46	-0.42	-0.34	-0.34	-0.34	-0.30	-0.12	-0.12	-0.06
Economy (with reweighting)	-0.64	-0.44	-0.41	-0.34	-0.34	-0.34	-0.31	-0.12	-0.12	-0.07
Poverty Gap										
Rural households	-0.26	-0.28	-0.17	-0.11	-0.05	0.00	0.04	0.08	0.11	0.14
Urban households (without reweighting)	-0.34	-0.28	-0.29	-0.28	-0.27	-0.26	-0.25	-0.24	-0.23	-0.21
Urban households (with reweighting)	-0.34	-0.28	-0.29	-0.28	-0.27	-0.26	-0.25	-0.24	-0.23	-0.22
Informal	-0.56	-0.38	-0.42	-0.40	-0.40	-0.38	-0.37	-0.36	-0.35	-0.34
Formal unskilled	0.01	-0.29	-0.20	-0.20	-0.19	-0.17	-0.15	-0.14	-0.12	-0.10
Formal skilled	0.06	0.06	0.08	0.08	0.08	0.08	0.09	0.10	0.11	0.12
Capitalists and rentiers	0.10	0.07	0.06	0.05	0.04	0.04	0.03	0.03	0.02	0.02
Economy (without reweighting)	-0.31	-0.28	-0.26	-0.23	-0.21	-0.19	-0.17	-0.15	-0.13	-0.12
Economy (with reweighting)	-0.31	-0.28	-0.25	-0.23	-0.21	-0.19	-0.17	-0.15	-0.14	-0.12
Overall Inequality [2]										
Gini-coefficient (without reweighting)	-0.0036	-0.0028	-0.0027	-0.0024	-0.0022	-0.0019	-0.0017	-0.0016	-0.0014	-0.0012
Gini-coefficient (with reweighting)	-0.0036	-0.0028	-0.0027	-0.0024	-0.0022	-0.0020	-0.0018	-0.0016	-0.0015	-0.0013
Theil-index (without reweighting)	-0.0076	-0.0062	-0.0058	-0.0052	-0.0047	-0.0042	-0.0037	-0.0033	-0.0029	-0.0026
Theil-index (with reweighting)	-0.0077	-0.0061	-0.0058	-0.0052	-0.0048	-0.0043	-0.0039	-0.0035	-0.0031	-0.0028
Beta-distribution approach with and without reweighting										
Poverty Headcount										
Rural households	-0.50	-0.53	-0.35	-0.24	-0.13	-0.03	0.05	0.11	0.17	0.22
Urban households (without reweighting)	-0.56	-0.55	-0.54	-0.52	-0.50	-0.48	-0.45	-0.42	-0.40	-0.37
Urban households (with reweighting)	-0.56	-0.53	-0.53	-0.51	-0.49	-0.47	-0.45	-0.42	-0.40	-0.38
Informal	-1.12	-0.76	-0.82	-0.79	-0.77	-0.74	-0.72	-0.69	-0.66	-0.63
Formal unskilled	-0.05	-0.88	-0.63	-0.63	-0.56	-0.51	-0.46	-0.41	-0.36	-0.30
Formal skilled	0.82	0.67	0.69	0.68	0.67	0.66	0.65	0.63	0.62	0.61
Capitalists and rentiers	0.82	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economy (without reweighting)	-0.55	-0.55	-0.49	-0.44	-0.39	-0.35	-0.31	-0.27	-0.24	-0.21
Economy (with reweighting)	-0.54	-0.53	-0.48	-0.43	-0.39	-0.35	-0.31	-0.27	-0.24	-0.21
Poverty Gap										
Rural households	-0.32	-0.34	-0.22	-0.15	-0.08	-0.02	0.03	0.07	0.11	0.14
Urban households (without reweighting)	-0.37	-0.35	-0.35	-0.33	-0.32	-0.31	-0.29	-0.27	-0.26	-0.24
Urban households (with reweighting)	-0.37	-0.34	-0.34	-0.33	-0.32	-0.30	-0.29	-0.28	-0.26	-0.25
Informal	-0.71	-0.48	-0.52	-0.50	-0.49	-0.47	-0.46	-0.44	-0.42	-0.40
Formal unskilled	-0.03	-0.52	-0.37	-0.37	-0.34	-0.31	-0.28	-0.24	-0.21	-0.18
Formal skilled	0.44	0.36	0.38	0.37	0.36	0.36	0.35	0.35	0.34	0.34
Capitalists and rentiers	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Economy (without reweighting)	-0.36	-0.35	-0.31	-0.28	-0.25	-0.23	-0.20	-0.18	-0.15	-0.13
Economy (with reweighting)	-0.36	-0.34	-0.31	-0.28	-0.25	-0.22	-0.20	-0.18	-0.16	-0.14
Between-group Inequality										
Theil-index (without reweighting)	-0.0085	-0.0068	-0.0064	-0.0058	-0.0052	-0.0047	-0.0042	-0.0038	-0.0033	-0.0029
Theil-index (with reweighting)	-0.0086	-0.0068	-0.0065	-0.0058	-0.0053	-0.0048	-0.0043	-0.0039	-0.0035	-0.0031

[1] Percentage deviations from baseline. [2] Gini Coefficients and Theil Indices measure between-group inequality.

Table A1
Observed and Fitted Poverty Measures
Using Estimated Shape Parameters of the Beta Distribution
includes outliers (out) and without outliers (no-out)

	Headcount Ratio			Gap Ratio		
Sectors	Observed	Fitted (out)	Fitted (no-out)	Observed	Fitted (out)	Fitted (no-out)
Rural	50.04	50.90	49.09	20.57	30.90	29.20
Urban Informal	43.35	51.59	45.66	17.41	31.69	26.57
Urban Formal Unskilled	32.16	37.89	36.48	13.03	21.39	20.62
Urban Skilled	4.44	14.88	9.60	1.15	7.50	4.99
Capitalist-Rentiers	3.33	4.66	0.00	0.40	2.44	0.00