GTAP-POV: A Framework for Assessing the National Poverty Impacts of Global Economic and Environmental Change

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Abstract

Increasingly economists are being called on to assess not only the national implications of global trade and environmental policies, but also the subnational consequences, including the impacts on low income and food insecure households. Bridging global, national and subnational scales within a single analytical framework presents great challenges. The purpose of this Technical Paper is to outline in detail one approach to this problem. By nesting a poverty module within the GTAP modeling framework, users are able to assess the impact of global trade and environmental policies, as well as prospective climate change, on poverty across seven different 'strata' or sub-populations within the focus countries. The application demonstrated here – that of multilateral trade reforms – demonstrates that the poverty impacts of global policies can be quite heterogeneous and sometimes unexpected.

Since the initial publication of this Technical Paper, others have sought to extend the sample of countries covered in the GTAP-POV module. This has led to the development of improved techniques for dealing with challenges posed by the household survey data. This revised version of the technical paper includes four appendices which provide STATA code to accomplish key steps in the process of constructing a GTAP-POV module for an individual country. We have also included a new section at the end of part 3 of the paper in which we compare patterns of poverty across the full range of countries available to us at this point in time. Our hope is that this Technical Paper will continue to inspire members of the GTAP network, as well as others, to contribute additional poverty modules. Eventually we hope to cover most developing countries. This would permit more definitive analysis of the poverty impacts of global economic and environmental policies.

JEL Classification: C54, D58, I32, Q12

Keywords: poverty analysis, household survey data, computable general equilibrium.

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1. Motivation

Predicting the effects of global trade and environmental policies, as well climate change, on developing-country poverty is a topic which has been in the policy spotlight over the past decade. The World Bank actively seeks to assess the poverty impacts of prospective trade and economic reforms for all least-developed countries (World Development Report 2000/2001). Under the United Nations' "Millennium Development Goals" the international assistance community committed to halve poverty by 2015 (United Nations Millennium Declaration 2000). Much of the debate over the Doha Development Agenda of the World Trade Organization has focused on the poverty impacts of current and prospective multilateral trade policies (Hertel and Winters 2006; Anderson et al. 2005; Winters 2003). The role of commodity price volatility in causing low-income households to move in and out of poverty has also received increasing attention (Ivanic and Martin 2008). More recently, international attention has begun to focus on the potential poverty impacts of climate change (see, for example, Ahmed et al. 2009; Hertel et al. 2010), and the policies aimed at mitigating greenhouse gas emissions (Hertel and Rosch 2010; Hertel, Burke and Lobell, 2010; Hussein, Hertel and Golub, 2013).

All of these economic questions share a common characteristic: the underlying changes being evaluated are fundamentally global in nature. Even if just a subset of the world's countries is involved in a given trade or environmental agreement, the impacts of these policies extend around the world. Yet poverty, the metric by which we seek to evaluate these policies, is fundamentally local in its causes and likely impacts. The purpose of this technical paper is to document a framework which can be used for linking global economic shocks to likely national poverty impacts across a wide range of developing countries. And although the motivation to develop the framework came from attempts to evaluate impact WTO reform proposals, the framework has since been used to look at other questions related to trade and environmental issues. These applications have been deemed worthy of publication in peer-reviewed journals, which is one criterion for judging a piece of research to be worthwhile. Box 1 below gives a partial listing of published studies employing the GTAP-POV framework. This technical paper draws liberally on the model exposition from these forgoing studies, seeking to gather in one place all the information needed for a user to replicate, supplement and extend this work to other regions and domains of application.

Box 1: Existing Studies Based on GTAP-POV Framework		
Motivation/Question	Reference	Finding
Impact of Doha development agenda on poverty headcounts in poor countries	Hertel, Keeney, Ivanic and Winters 2009: "Why Isn't the Doha Development Agenda more Poverty Friendly?"	Due to the exclusion of LDC trade reforms the DDA is less poverty friendly than the policies omitted from that proposal
Impact of policy on calorie intakes of poor	Verma and Hertel 2009: "Commodity Price Volatility and Nutrition Vulnerability"	Special safeguards do not improve the calorie intake distribution for the poor in Bangladesh
Impact of climate *volatility* on poverty	Ahmed, Diffenbaugh and Hertel 2009: "Climate volatility deepens poverty vulnerability in developing countries"	Current climate extremes increase poverty across a sample countries; urban wage earners are the most vulnerable
Impact of climate *change* on poverty	Hertel, Burke and Lobell 2010: "The poverty implications of climate-induced crop yield changes by 2030"	Expected climate change by 2030 has only modest poverty impacts; however, poverty increases are significant under 'worst case' scenario
Impact of trade facilitation on poverty	Stone, Strutt and Hertel 2010: "Assessing Socioeconomic Impacts of Transport Infrastructure Projects in the Greater Mekong Subregion"	Strong poverty reductions in the region as a result of infrastructure development and trade facilitation in the Mekong region
Poverty impacts of trade reform in the context of commodity market volatility	Verma, Hertel and Valenzuela 2011b: "Are The Poverty Effects of Trade Policies Invisible?"	Short-run poverty impacts of full trade liberalization for staple grains worldwide are largely invisible when viewed against the backdrop of normal commodity market volatility
Poverty impacts of climate mitigation policies	Hussein, Hertel and Golub 2013: "Climate Change Mitigation Policies and Poverty in Developing Countries."	Climate mitigation policies could be poverty increasing if they include aggressive carbon pricing of tropical forests.

1.1. Key Linkages from International Trade to Poverty

The links between global economic shocks and poverty have been most thoroughly discussed in the context of international trade policy. Winters 2000 is a key reference in this regard. His work highlights the importance of the following channels through which poverty might be affected: (a) the consumer price and availability of goods; (b) factor prices and quantities employed; (c) government taxes and transfers influenced by changes in revenue from trade-related taxes; (d) the terms of trade and other external shocks; (e) incentives for investment and innovation that affect long-run economic growth; (f) remittances; and (g) short-run risk and adjustment costs. Most studies in the literature focus on only one or two of these links and abstract from the rest.

Consumer prices have received the most attention. Concern about impacts of higher food prices/reduced food availability has also dominated discussions surrounding recent commodity price change (Ivanic and Martin 2008) as well as climate change. Coverage of links (b) through (g) is more uneven. For example, a study by Levin 2000 focuses on transfers, link (c). An increasing number of studies emphasize long-run growth as the primary vehicle for poverty reduction (Anderson, Martin and van der Mensbrugghe 2005; Cline 2004; Dollar and Kraay 2004). Most economy-wide analyses account for terms of trade effects, link (d).

General equilibrium analyses of trade policy and poverty usually emphasize link (b) – the importance of factor prices, income, and employment for poverty[7] (see for, example, the collection of papers on the poverty impacts of the WTO's Doha Development Agenda in the 2006 volume edited by Hertel and Winters). Two households may have identical consumption patterns and income levels, but entirely different *sources* of income; for example, one might derive all its income from agricultural self-employment, while the other relies on transfers from a relative who works abroad. Ravallion and Lokshin 2000, in their study of prospective trade reforms in Morocco, distinguish *vertical inequality* (impacts on households at different income levels) from *horizontal inequality* (impacts on households at the same initial income level). They find that the latter tends to dominate in their analysis of the impact of trade reforms on income distribution. Bouet, Estrades and Laborde (2011) conclude the same thing in their study of trade liberalization in five developing countries. Similarly, in their analysis of climate change impacts on poverty, Hertel et al. 2010 emphasize the differential impacts on self-employed households in the farm and non-farm sectors having similar income levels.

The GTAP-POV approach does not claim to cover all the channels influencing impacts of global change on poverty. In its present form seeks only to deal with links (a) – (d) in a consistent and comprehensive fashion. And, as we will see, the approach to household stratification is fundamentally short- to medium-run in nature. As such it is not well suited for dealing with long run issues of investment, innovation and economic growth. Also, while it tracks transfers as a source of household income, it does not distinguish domestic from international remittances, and public from private transfers. As such, it does not deal very effectively with (f). Finally, since the model does not incorporate risk, it also ignores link (g).

1.2. Justification for the Approach

The specific approach to understanding the poverty impacts of trade policy embodied in GTAP-POV evolved out of limitations identified in the context of a major research project on this topic summarized in the volume edited by Hertel and Winters (2006). This included a dozen country case studies, as well as several global economic analyses. The country case studies involved a mix of partial and general equilibrium modeling efforts – some econometric-based and others using computational approaches. They yielded some key policy insights. For example, the study focusing on the Brazilian poverty impacts of rich country agricultural reforms showed that, even though wealthy Brazilian landowners benefited greatly from these

[7] The importance of this point frequently arises in classical trade theory. For instance, by the Heckscher-Ohlin theorem, a country has a comparative advantage in the good that intensively uses the country's relatively abundant factor. Free trade increases the relative price of that good, and that in turn, by Stolper and Samuelson's (1941) theorem, it increases the real return of the relatively abundant factor by an even larger percentage. Thus changes in commodity prices tend to *magnify* the impact on factor prices (Jones, 1965; 1971). This effect is particularly strong in the short run when some factors are sector-specific.

reforms, the beneficial impacts on unskilled wages and employment were sufficient to reduce overall inequality and also reduce poverty in Brazil. This was a very important finding and caught the attention of policy makers who then asked the question: "Is Brazil an anomaly? Can you generalize these results across all developing countries?"

The Brazilian results were arrived at via some rather sophisticated, single country, micro-simulation modeling of the sort that could not be readily extended to a large number of other countries. On the other hand, the multi-country studies, based on simple, aggregate, poverty-income elasticities, were too simplistic to permit such statements. Hence the search for a framework which is rich enough to capture household heterogeneity within and across countries, yet which at the same time is simple enough to analyze, explain, compare and permit computation of international summary statistics. The goal is to facilitate more general statements such as: "The specific reforms undertaken in the Doha Development Agenda are less poverty-friendly than those *not undertaken* in this Agenda." Indeed, the first application of the GTAP-POV framework evaluates this statement (Hertel et al., 2009). The goal of this technical paper is to make this framework widely available and to encourage others to develop 'modules' for their own countries, thereby expanding overall country coverage.

It should be emphasized that this is necessarily a *simple framework*. Indeed, it is the simplest model that could be designed and implemented with data from a wide variety of countries, capturing key differences in poverty across countries, while abstracting from region-specific eccentricities in statistics and economic markets (or the lack thereof). *This framework is not a substitute for a full-blown, micro simulation model of poverty* of the sort alluded to above in the case of Brazil. This is a complement to such studies, and may be used either: (a) before undertaking such a detailed country case study to see whether there are potential poverty impacts worthy of deeper investigation, or (b) after undertaking a detailed case study, as with the Doha reform example, in order to see whether the country specific results carry over to other countries, albeit within a simplified framework.

It should be noted that several alternative, global economic models with income distribution have recently emerged. Each one offers an alternative approach to eliciting the distributional impacts of global economic policies. The Global Income Distribution Dynamics (GIDD) framework developed by Bussolo, Hoyos, Medvedev and van der Mensbrugghe at the World Bank links CGE model results for wages to a set of household surveys and aims to fully characterize the household income distribution at global scale. They use this to investigate the distributional impacts of climate change (2008) as well as trade policies (2009). The idea of being able to track the global income distribution is very ambitious, but also very appealing. Unfortunately, this framework does not lend itself to distributed development/implementation in the way envisioned for GTAP-POV. As of this writing, GIDD also draws only on wage and food price information from the CGE model.

In recent research undertaken at IFPRI, Bouet, Estrades and Laborde (2011) have disaggregated households in the MIRAGE model for multiple countries. Their approach is designed to integrate modeling and data base management in such a way as to permit researchers to alter the household aggregation used in any particular study. They incorporate all the households into their CGE model directly and therefore attain a full, micro-macro synthesis. At present it is not yet portable to other research groups, but with time and sufficient resources, this offers a very attractive solution to the problem of assessing the distributional impacts of economic policies. Nonetheless, even with such a full-blown, micro-macro model in hand, the equations in the GTAP-POV module offers a handy way to understand and interpret results from the more elaborated model. In short, we believe that *the GTAP-POV approach is an excellent entry point for researchers already familiar with the GTAP modeling framework, who wish to begin thinking about the poverty impacts of policies* before graduating on to their own more complex approaches.

1.3. Adapting GTAP-POV to Your Country

As a multi-country framework, GTAP-POV will become more valuable to users as more countries are included the underlying data sources are brought up-to-date using the latest household surveys. Herein lies a collective action problem, born of these network externalities. It takes a significant amount of time to develop an individual country module for GTAP-POV. Depending on prior familiarity with the national household survey being used, as well as familiarity with the GTAP-POV framework, implementation for a new country could take anywhere from several weeks to several months. And the payoff for any given individual to develop this, as opposed to developing their own, individualized, national model, is limited unless there are other countries in the data base to enable broader comparisons.

At inception, the GTAP data base faced this same problem. The first data base consisted of just 12 regions with the 13th comprising a rest of world aggregate. Version 9 of the GTAP data base now contains 140 regions, with the country coverage continually expanding. How has this been accomplished? Individual contributors to the collective good are rewarded in three ways: (a) they receive the resulting data base for free, (b) furthermore, they are placed on the inside track for data base pre-releases, a privilege that puts them on equal pre-release footing with GTAP consortium members, and (c) they receive a fully consistent GTAP data base with their own country broken out/updated – something which would be quite difficult to accomplish on one's own.

With GTAP-POV we seek to establish some similar incentives for overcoming this collective good problem. In particular, for those authors who successfully contribute a fully documented GTAP-POV data base, we stand ready to disaggregate and calibrate the model to this new data base so that the author can use it for her/his own analysis. By having it incorporated into the full GTAP-POV framework, they can undertake international comparisons, thereby gaining additional insight into differences and similarities between their focus countries and others in the GTAP-POV sample.

The technical paper is organized as follows. We next turn to the simple analytical framework which has been developed for estimating poverty impacts of global policies. This includes a description of the equations for determining income and spending effects, as well as the data and econometric estimates underpinning household consumption behavior. Calibration procedures are also discussed. Section 3 turns to the specific procedures used to process household survey data for incorporation into the income module of GTAP-POV. This section, along with the STATA code in the appendices, comprises the 'user's manual' for those wishing to add a new country to GTAP-POV. It concludes with a comparison of the composition of poverty across the 31 different regions which have been processed to date. Finally, the paper concludes with a discussion of the original GTAP-POV application to analyzing the poverty impacts of a WTO agreement (Section 4). Section 5 concludes.

2. Analytical Framework Overview

There are many alternative approaches to estimating the change in poverty due to trade reforms (Winters et al. 2004; Hertel and Reimer 2005). The analytical approach used here builds on that initially laid out in Hertel et al. 2004, and subsequently simplified in Hertel et al. 2009. It is based on a macro-to-micro modeling strategy in which a micro-simulation household model is embedded in the global model; however there is no feedback from micro to macro dimension. This is potentially problematic on two counts. Firstly, if the policy being simulated were to result is a significant change in the distribution of purchasing power amongst households, and if these households have significantly different patterns of spending, then the change in income distribution could alter relative prices in the economy. To date, we are not aware of any static simulations of micro-macro models which have shown this to be an important consideration. To the contrary, it appears that most policies under serious consideration do not result in much redistribution of income. (Perhaps this is not surprising if one takes a political economy view of policy reforms.) Furthermore, the broad differences in spending patterns across household groups are rarely enough to generate significant commodity price impacts, even if there were to be substantial income redistribution. In short, the robustness of general equilibrium price changes to the disaggregation of households is a direct result of the robustness of income distribution to comparative static policy shocks as well as the relatively similar spending patterns across broad household groups.

The second limitation of our macro-to-micro modeling approach is that it does not require full reconciliation of the two data bases. In our view, this is a more serious concern. At this point, most authors seeking such reconciliation are reduced to making some arbitrary adjustments, which themselves may have significant impacts. For example, Ivanic (2004) finds that household surveys tend to report far less capital income than is revealed in the survey data. This is typically due to under-sampling of wealthy households, as well as underreporting of earnings from capital. This leaves a large portion of capital to be allocated to households. Should it be given just to the rich households? Should it be spread across all households? These decisions can have far reaching implications for the poverty results. We believe they must be addressed, but we do not believe that GTAP-POV is the appropriate place to start this challenging task. Rather, it must be undertaken in conjunction with those building the national income accounts.

The poverty analysis presented here relies on simulating household welfare at the poverty line for different segments (strata) of the population. Household welfare and the associated consumption decisions are arrived at by maximizing the household's utility function subject to their budget constraint, where the latter is influenced by their endowment composition, as revealed in household survey data. For any given level of goods and factor prices the system gives us the levels of consumption demands and associated utility.

Alternatively, for any change in commodity prices, it is possible to compute the expenditure required to allow a household to remain at the initial level of utility. This initial level of utility at the poverty line[8] is defined as the *poverty level of utility.* We refer to this required change in expenditure as the change in the 'true cost of living at the poverty line'. Using this true cost of living we can deflate the nominal income change arising out of the new factor prices, to obtain the change in real income, by stratum. This change in real income coupled with information about the stratum elasticity of poverty headcount with respect to real income, enables us to predict changes in poverty headcount by stratum.

2.1. Elasticity Approach to Poverty Headcount

With our emphasis on the poverty headcount, it is the households in the proximity of poverty line that are likely to see a change in their poverty status following a policy stimulus. Therefore, we focus squarely on the households in the *neighborhood* of the poverty line making use of the *disaggregated* poverty elasticity approach. We have chosen to focus on households in the neighborhood of the poverty line in order to permit generalization of impacts across countries. An alternative would be to explore the impacts on all households within a single country. For practical purposes, unless otherwise noted, the neighborhood is defined as the decile (10 percent of the stratum sample) around the poverty line. Our analysis begins with the cumulative density function of per capita income in region r for the population stratum s : $F_{rs}(y)$. Thus $F_{rs}(\bar{y}_r^p)$ computes the poverty headcount ratio when $\bar{y}_r^p$ is the level of income required at initial equilibrium prices, to attain the poverty level of utility in region r. We assume that preferences and consumer prices are the same across all strata in the country. Therefore, the initial levels of poverty income, consumption and utility are the same for all households in a given country.[9]

As noted above we are interested in the elasticity of the poverty headcount with respect to a small change in the real income of households at the poverty line in a given stratum s: dy_{rs}^p. Assuming unchanging commodity prices, and a differentiable function, $F_{rs}(\bar{y}_r^p)$, this may be computed as follows:

$$\varepsilon_{rs} = -\frac{dF_{rs}(\bar{y}_r^p)/dy_{rs}^p}{F_{rs}(\bar{y}_r^p)/y_{rs}^p} \qquad (1).$$

Table 1 reports these stratum-specific poverty elasticities for fifteen countries underpinning the Doha analysis in Section 4 of this paper. . Estimates of ε_{rs} are between 0.0006 (for agriculturally self-employed in Zambia) and 8.9 (for rural labor in Vietnam), varying

[8] The definition of poverty line used can differ with the study objective e.g. one can use World Bank's definition (historically \$1/day, but now either \$1.25/day or \$2/day) for cross country comparison purposes whereas the national poverty line may be more appropriate for national policy analysis.

[9] This is clearly an important limitation, as we expect prices and potentially consumer preferences, to vary within most countries. To the extent that consumption patterns differ across strata (e.g., rural vs. urban) GTAP-POV will miss the resulting differential incidence on the consumption side. However, we expect such deviations to be small, relative to differences in earnings patterns.

widely by stratum and country in the sample. Details about derivation of these arc elasticities are outlined in section 3.2 below.

The proportional change in real income of households at the poverty line in stratum s of region r can be written as the income–share weighted sum of the households' real after-tax factor earnings:

$$\hat{y}^p_{rs} = \sum_j \alpha^p_{rsj}(\hat{W}_{rj} - \hat{C}^p_r) \qquad (2),$$

where α^p_{rsj} is the share[10] of income obtained from factor j by households at the poverty line in stratum s of region r; $\hat{W}_{rj}$ is the proportional change in *after-tax* earnings of factor j in region r, and $\hat{C}^p_r$ is the proportional change in the true cost of living at the poverty line in region r. As noted previously, this is obtained by solving for the level of expenditure required to *remain at the initial poverty level of utility*, given the new configuration of commodity prices and optimal demands. We can now express the proportional change in the poverty headcount in stratum s of region r as follows:

$$\hat{F}_{rs}(\bar{y}^p_r) = \hat{H}_{rs} = -\varepsilon_{rs} \cdot \hat{y}^p_{rs} = -\varepsilon_{rs} \cdot \sum_j \alpha^p_{rsj}\,(\hat{W}_{rj} - \hat{C}^p_r) \qquad (3).$$

Having established the determinants of the stratum poverty headcount, we can now progress to the national poverty headcount, which can be expressed as a function of the stratum headcounts and stratum population (POP_{rs}): $H_r = \left[\sum_s POP_{rs} * H_{rs}\right] / POP_r$, where $POP_r = \sum_s POP_{rs}$. So the proportional change in H_r is given by: $\hat{H}_r = \sum_s \beta_{rs} * \hat{H}_{rs}$, where the share of stratum s poverty in nationwide poverty in region r is computed as: $\beta_{rs} = \left[\left(POP_{rs} * H_{rs}\right)/POP_r\right]/H_r = \left(POP_{rs} * H_{rs}\right)/\sum_k\left(POP_{rk} * H_{rk}\right)$. These stratum poverty shares are reported in Table 2. One can confirm from the table that, with a few exceptions, the agriculture specialized households and rural diversified households tend to dominate the poorest households' poverty headcount. Notable exceptions are Pakistan and Venezuela where self-employed, non-agriculture and urban labor households contain a large share of the poor.

[10] More details about these shares are provided in section 3 of this paper.

Table 1. Income Elasticity of Poverty Headcount (At $1/Day)

Country	Strata							
	Agriculture	Non-Agric.	Urban Labor	Rural Labor	Transfer	Urban Diverse	Rural Diverse	Total
Bangladesh	1.64	2.02	1.58	0.63	0.56	1.74	1.09	1.24
Indonesia	2.35	2.14	2.38	2.89	1.17	2.58	2.87	2.47
Philippines	2.25	1.96	2.98	2.44	1.69	2.42	1.98	2.15
Thailand	2.30	2.42	2.98	2.45	2.78	2.42	2.59	2.57
Vietnam	0.48	1.12	2.81	8.98	0.84	0.86	1.01	0.98
Bolivia	0.17	2.43	4.53	2.67	1.52	1.16	0.79	0.77
El Salvador	0.86	1.35	27.30	2.20	0.10	7.65	0.91	2.98
Guatemala	0.38	1.00	0.02	0.60	0.29	0.49	0.50	0.49
Honduras	0.83	0.97	12.24	1.66	0.71	1.39	1.07	1.33
Nicaragua	0.37	0.54	1.23	0.88	0.36	0.92	0.73	0.67
Panama	0.74	4.66	1.91	2.90	0.90	2.50	1.32	1.52
Costa Rica	0.26	0.34	0.04	0.67	0.39	0.01	0.06	0.21
Paraguay	0.38	1.34	2.61	2.23	0.42	0.23	1.18	0.80
Chile	0.03	0.02	0.13	0.35	0.85	0.00	0.01	0.28
Colombia	0.64	0.73	0.00	0.80	0.61	0.00	0.19	0.33
Dominican Rep	0.56	1.56	1.99	3.85	0.39	0.05	0.55	0.58
Brazil	0.84	0.58	6.76	6.46	5.56	0.00	0.39	0.30
Ecuador	0.58	1.68	0.02	2.27	0.05	0.05	0.44	0.49
Jamaica	1.31	0.01	0.15	0.71	n/a	0.15	0.02	0.23
Peru	0.50	0.88	0.51	0.53	n/a	0.02	1.07	0.63
Venezuela	1.17	0.98	29.12	1.77	1.01	0.05	0.65	3.75
Uruguay	0.14	0.75	n/a	n/a	0.28	0.02	0.06	0.15
Mexico	1.48	0.25	0.12	0.59	0.40	0.01	0.04	0.27
Malawi	0.49	0.30	2.26	1.97	0.43	1.04	0.76	0.58
Mozambique	0.28	0.94	0.97	0.76	0.48	1.58	0.99	0.64
Uganda	0.28	0.40	1.71	0.34	0.01	0.36	0.21	0.24
Zambia	0.00	0.64	2.28	0.91	0.45	1.29	0.37	0.61

Source: Authors' calculations
Notes: Poverty elasticities for the LAC region are evaluated at the $1.25/day poverty line. Missing elasticities for Jamaica are due to lack of data. Missing elasticities for Peru and Uruguay are due to the absence of poor in the strata.

Using (3), the change in the national poverty headcount in response to a small change in factor and commodity prices can be expressed as:

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^p \, (\widehat{W}_{rj} - \hat{C}_r^p) \qquad (4).$$

For some purposes, it is useful to further separate the tax component associated with the replacement of lost tariff revenue by another tax instrument. Hertel and Winters (2006) find that the choice of a revenue-replacing tax instrument can have a significant impact on the poverty results following trade reform. Here, we follow those authors in adopting the neutral approach of applying an endogenous, uniform factor income tax. Define the uniform *ad valorem* income tax on factor *j* in region *r* as follows: $TAX_{rj} = t_r W_{rj}^m \cdot L_{rj}$, where t_r is the tax replacement instrument operating on market earnings, W_{rj}^m. Letting $T_r = (1+t_r)$ be the *power* of the replacement income tax in region *r*, then with fixed endowments, the proportional change in after-tax income is given by: $\hat{W}_{rj} = \hat{W}_{rj}^m - \hat{T}_r$. Substituting into (4) we have the following *decomposition* of changes in the poverty headcount in region *r into after-tax earnings*, *replacement tax*, and *cost of living components*:

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^p \, (\widehat{W}_{rj}^m - \hat{T}_r - \hat{C}_r^p) \qquad (5).$$

Finally, since only relative prices matter in the general equilibrium model, and since we wish to separately discuss the "earnings" and "spending" effects of trade reform on households, it is useful to normalize both market wages and the cost of living by a common variable. The choice of normalization factor is arbitrary, since we will first subtract it from wages, then add it back into the cost of living term. The normalization variable should be a national, nominal variable that does not vary by stratum or earnings type, and, for the decomposition to be useful, it should have some economic meaning when compared to a particular category of wages, or to the cost of living. For the present analysis, we choose net national income in the region, y_r. Subtracting and adding $\hat{y}_r$ to the term in brackets in (5), recognizing that the tax replacement and cost of living effects are independent of stratum and earnings type, and making use of the fact that $\sum_j \alpha_{rsj} = 1$, we define the national poverty elasticity as the poverty share-weighted sum of the stratum elasticities: $\varepsilon_r \equiv \sum_s \beta_{rs}\varepsilon_{rs}$. This gives the final decomposition of the national poverty impacts of policy intervention:

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha_{rsj}^p \left(\widehat{W}_{rj}^m - \hat{y}_r\right) + \varepsilon_r \cdot \hat{T}_r + \varepsilon_r(\hat{C}_r^p - \hat{y}_r) \qquad (6).$$

The first term in (6) is termed the "earnings effect" and identifies the change in a particular wage, relative to net national income. The negative sign in front of this term denotes the fact that higher earnings result in a poverty reduction. The second term is the "tax effect". *Ceteris paribus*, higher taxes result in greater poverty. And the third term is the spending effect, which identifies the change in cost of living at the poverty line, relative to net national income. When the cost of living rises, poverty also increases.

One can use (6) to consider the effects of an increase in (a) the unskilled wage rate, (b) the power of the tax, and (c) the price of staple foods. If unskilled wages represent an important part of income for (i.e. $\alpha_{rsj}^{p} \gg 0$, where j = unskilled wage), rise in the unskilled wage rate relative to y_r will boost income for the households with higher concentrations of unskilled labor, moving some across the poverty line. The proportional change in stratum headcount will depend on the density of the stratum population in the neighborhood of the poverty line as captured by ε_{rs}. If this density is high, and the stratum also contains a substantial share of the nation's poor as captured by β_{rs}, then there will be a relatively large reduction in the poverty headcount *ceteris paribus*.

A different kind of policy, say a tariff cut, may require a replacement tax to make up for the lost revenue. In this case we expect a rise in the income tax, which, if levied on the poor, such that ($\hat{T}_r > 0$), will induce a counter-acting rise in poverty. With a rise in staple food prices we expect a rise in the cost of living at the poverty line relative to net national income and therefore a rise in poverty in region *r*. Since most trade reforms change all the relative prices as well as tax revenues, the net effect on poverty in a given stratum is not at all clear. Therefore, the decomposition offered by (6) is important for understanding the drivers behind a change in the stratum and national poverty headcounts. The general equilibrium framework that determines how these factor prices, commodity prices and taxes change as a function of trade policies, is described in the next section.

2.2. The Global General Equilibrium Model

Documentation of the standard GTAP model is available from other sources (e.g. Hertel, 1997). However, in addition to adding equations (1) - (6) to the model, several important modifications have been made to the standard GTAP model in order to enrich the results when it comes to understanding the distributional impacts of trade and environmental policies. On the demand side, it is necessary to incorporate additional demand systems for households at the poverty line in each poverty region. These demand systems are solved for changes in the real cost of living at the poverty line, which is a necessary input into equation (6).

Factor market segmentation is a key consideration on the supply side. Given the continuing predominance of poverty in rural areas of most developing countries, as well as the importance of agriculture as a major economic activity in the poorest rural regions, special attention must be paid to the segmentation of labor and capital markets between the farm and non-farm sectors. GTAP-POV follows the work of Keeney and Hertel 2005 in modeling farm/non-farm mobility by specifying a constant elasticity of transformation function which "transforms" farm-labor into non-farm labor and vice-versa. Imperfect transformation of labor between these sectors permits wages to diverge between the farm and non-farm uses. The same approach is applied to capital, postulating a transformation function between agricultural and other capital. Segmented factor markets ensure that the impact of reduced subsidies to agriculture in the rich economies or reform induced higher farm prices in developing countries, will not be shared equally between the farm and non-farm factors of production. In order to parameterize these Constant Elasticity of Transformation (CET) factor mobility functions Keeney and Hertel (2005) draw on the OECD

2001 survey of agricultural factor markets. This presents a very important limitation, since the OECD survey includes Mexico, but no lower income economies. Developing country-specific estimates for these factor mobility parameters should be a high priority for anyone developing a GTAP-POV module for a new region.

There is also the question of unemployment. Research by previous authors (Bussolo et al. 2006; Robilliard and Robinson 2006) shows that it can be important to take account of which workers/households gain employment in an expanding economy, and which ones lose their jobs in a shrinking labor market. Unfortunately, handling this issue properly involves estimation of a queueing model of labor markets, which predicts which individuals are most likely to be re-employed or fired as the aggregate demand for labor expands or contracts. Translating these employment changes into household well-being requires mapping individual workers to households. This is well beyond the scope of GTAP-POV. Instead, the GTAP-POV model assumes a constant level of aggregate land, labor, and capital employment reflecting the belief that aggregate employment is determined by factors such as macro-economic policies, labor market norms and regulations, all of which are largely independent of the trade and environmental policies examined within the GTAP framework. Accordingly, any increase in demand for labor will be reflected in higher wages, and these will benefit individual households in proportion to their endowment of the particular type of labor in question.

2.2.1. Macro-Economic Closure

The macro-economic closure in a CGE model involves determining the split between exogenous and endogenous variables. With the focus in this Technical Paper being on the welfare of individual households within the country, and not on aggregate regional welfare, we seek a closure that will place a clear emphasis on utility derived from private consumption. We therefore employ a macroeconomic closure which fixes the ratios of government spending, tax revenue, net national savings, and the trade balance, all relative to net national income.

The logic behind this closure may be developed as follows (see also the technical appendix to Hertel et al. (2007). Begin with the following disposition of net national income:

$$Y = C + S + G \tag{7),}$$

where Y = net national income, C = private consumption expenditure, S = net national savings (public and private savings combined), and G = government spending. Now solve for consumption as a function of the other variables to obtain the following expression for private consumption:

$$C = Y\left(1 - \frac{S}{Y} - \frac{G}{Y}\right) = \kappa Y \tag{8),}$$

where κ = the marginal propensity for private consumption out of net national income (NNI). If we fix the ratio of savings to NNI and also the ratio of government spending to NNI, then κ is also fixed under this closure. In proportional change terms, this implies that real private consumption, $\hat{Q}^C$, will rise if either the price of private consumption falls ($\hat{P}^C < 0$) or net national income rises ($\hat{Y}^{C} > 0$). These variables are easily mapped to the disaggregated households, thereby facilitating the linking of aggregated and disaggregated welfare impacts of trade reforms.

There is a further implication of this closure rule that is also advantageous. This may be seen by normalizing the external balance condition, dividing through by net national income to get:

$$\frac{(S-I)}{Y} = \frac{(X-M)}{Y} \qquad (9).$$

By fixing the trade balance relative to net national income, the right hand side of this equation is also fixed in our closure. Since *S/Y* is also fixed, therefore, *I/Y* is fixed by implication. Of course, real investment, $\hat{Q}^{I}$, does vary in this closure. It rises when the price of capital goods falls, or when *Y* rises. This seems reasonable to us.

There is yet a third important benefit associated with this closure option pertaining to the treatment of transfer payments. In a simplified view of the world, public transfer payments to private households can be viewed as the difference between taxes and government spending on real goods and services: $Trans = T - G$, or, dividing through by net national income, *Y*:

$$\frac{Trans}{Y} = \frac{T}{Y} - \frac{G}{Y} \qquad (10).$$

Since *T/Y* is fixed under our tax replacement closure, and *G/Y* is fixed, the left hand side of this equation is also fixed. Thus, even though transfer payments *(Trans)* are not explicitly modeled in GTAP-POV, we know that it must implicitly change in proportion to *Y*. Therefore we index transfer payments in the model to net national income, thereby ensuring that the relationship in (10) is maintained.

2.2.2. Household Stratification[11]

A key finding from the applications of GTAP-POV identified in Box 1 is the importance of stratifying households by their primary source of income. Farm households in developing countries often rely on the agricultural enterprise for virtually all of their income. The share of national poverty concentrated in agriculture-specialized households is quite high in the poorest of the countries examined in this Technical Paper. Based on Table 2, between one-quarter and one-half of the $1/day headcount in Chile, Colombia, Indonesia, Malawi, Mozambique and Zambia comprises agriculture-specialized households. Not only are farm households in the poorest countries more likely to be specialized in farming, these specialized farm households also tend to be poorer, on average, than the rest of the population. The implication of this pattern of farm income specialization is that the poorest households in the poorest countries are more concentrated in agriculture and therefore more likely to benefit from producer price increases engendered by multilateral trade reforms. Based on Hertel et al. 2004, the framework distinguishes five household

[11] This section draws heavily from previous papers, including: Hertel et al 2009 and Hertel et al., 2004.

groups that rely almost exclusively (95% or more) on one source of income: agricultural self-employment, non-agricultural self-employment, rural wage labor, urban wage labor, or transfer payments. The remaining households are grouped into rural and urban diversified strata, giving seven total earnings strata.[12] More details on stratifying the households are given in section 3.1.1.

2.2.3. Imputation of Factor Earnings

Implementation of the poverty headcount equation (6) requires us to map factor earnings in the general equilibrium model to household income sources. Agricultural labor and capital receive the corresponding farm factor returns from the general equilibrium model; just as non-agricultural labor and capital receive non-farm returns. Wage labor for diversified households reported in the surveys presents a problem because information is lacking to allocate it between agricultural vs. non-agricultural activities. We simply assign to it the composite wage for all labor entering into the CET endowment function. Finally, as per our macro-economic assumptions explained above, transfer payments are indexed by the growth rate in net national income. More details on the imputation of factor earnings are provided in section 3.3 of this paper but before that we must discuss the characterization of household consumption demand.

2.2.4. Household Consumption Demand

Thus far we have only discussed the earnings side of the poverty calculation. However, implementation of (6) also requires us to track changes in the real cost of living at the poverty line. In order to do so, we must be able to predict consumption patterns at low levels of income in both the baseline and the policy reform scenarios. Unfortunately, there is no perfect household demand system – different demand systems have different advantages. For example, the Constant Difference of Elasticities (CDE) demand system that represents aggregate private consumption in the standard GTAP model was chosen due to its ease of calibration to vectors of national-level income and own-price elasticities of demand. Having reasonable elasticities governing aggregate demand behavior is critical for generating valid model behavior in the face of exogenous shocks to demand, supply or policies (Beckman et al. 2011). However, the CDE does not include subsistence terms – a feature that is important when trying to predict expenditure patterns at very low levels of income. Households cannot simply eliminate consumption of staple grains, if the price rises; they cut back on consumption of non-essential items. The subsistence term reflects a level of consumption that is essential for household survival.

In order to predict consumption patterns at the poverty line, we borrow from Rimmer and Powell's (1996), An Implicit Directly Additive Demand System (AIDADS) demand system to represent consumer preferences. AIDADS is particularly useful for poverty analysis because it includes not only a subsistence term for each commodity, but also a parameter which dictates marginal expenditure patterns at low levels of income. Together these two terms provide critical information needed to understand consumption behavior at the poverty level. Additional

[12] A clear limitation of this approach stems from the rigidity of a given households' classification by earnings specialization. Obviously households may be induced to change their specialization or diversify in response to changing relative factor returns. We believe that the relatively broad definition of strata circumvents this problem for the majority of households in the face of modest earnings changes. However, this important qualification will be further considered below in the results section.

advantages of AIDADS include the fact that it lends itself to international cross-section estimation and can be estimated directly on the GTAP data base, thereby circumventing the need to potentially problematic mapping from consumer to producer goods (Reimer and Hertel, 2004). AIDADS has been shown to perform well in out of sample forecasting of international food consumption patterns (Cranfield et al. 2003). In addition, Verma et al. (2011a) show that, in the case of Bangladesh, a version of AIDADS estimated using international cross-section data performs quite well in predicting food consumption behavior across the entire income spectrum. This latter finding is particularly important in the context of GTAP-POV, as we will use the demand system, estimated based on international cross-section data, to predict consumption shares at the poverty line in each of the poverty regions.

The AIDADS system predicts budget shares as the sum of subsistence and discretionary budget components:

$$\lambda_n = \frac{p_n \gamma_n}{y} + \frac{\alpha_n + \beta_n \exp(u)}{1 + \exp(u)} \left(1 - \frac{p'\gamma}{y}\right) \quad \forall\, n \tag{11),}$$

where λ_n is the budget share of good n, α_n, β_n, and γ_n are unknown parameters, u represents utility, p_n is the price of good n, and y is income. We draw on the methodology of Cranfield et al. 2002 and Cranfield et al. 2004 to obtain initial parameter estimates. The subsequent calibration for individual countries is adapted from Golub 2006. Interested readers may obtain the estimation and calibration code (implemented in GAMS) from the authors. However, given the complexity of this step, and the relatively high degree of automation, we offer to provide authors with the calibrated AIADS estimates for their individual country. Readers who wish to change the grouping of final goods may want to perform their own estimation/calibration, but this will involve some investment of time and expertise.

2.3. Obtaining the Poverty Level of Utility

Having obtained the country-specific AIDADS calibrated estimates, describing *per capita* national consumption, we need to tailor this to the poverty line of interest. To do so, we fix consumer prices, and shock per capita expenditure by the country specific scalar necessary to reach the poverty line. For example, if the \$1/day poverty income is 30% of per capita national income, then we shock per capita expenditure in the AIDADS system downwards by 70%. The new demand system produces new levels of utility, consistent with the poverty level of income. The poverty levels of utility, associated consumption levels and the calibrated AIDADS parameters for the country in question are then read into the GTAP-POV model. The AIDADS estimates used in the application in Section 4 are based on GTAP version 6 data and can be found under headers ALPH, BETA, GAMM and UP (α, β, γ *and* u respectively, in equation 11) in the default.prm file in the application. These estimates serve to determine changes in the real cost of living at the poverty line in the face of economic shocks.

2.3.1. Characterizing National and Poverty Level Demand

Recall that since GTAP-POV is a macro-to-micro simulation model, without feedback from disaggregate consumption behavior to aggregate demand, we retain the national, per capita demand system in the model. It is this demand system that contributes to equilibrium price changes, not the AIDADS demand systems used at the poverty line. In order to ensure full consistency between the macro- and micro-behavior, the original work with GTAP-POV (e.g. Hertel et al. 2004) used the same AIDADS demand system to characterize per capita national demands as is used for predicting consumption behavior at the poverty line. This consistency is appealing from a theoretical point of view. However, it does change the behavior of the economic model. And for this reason subsequent authors have sometimes chosen to leave the original CDE national demand system in place, while retaining the AIDADS estimates of consumption at the poverty line (Verma, Hertel and Valenzuela, 2011). We refer to these two competing specifications as the CDE-AIDADS and AIDADS-AIDADS specifications[13], respectively. The former permits the poverty module to be simply added at the bottom of the model without implications for the marginal behavior of the overall model. In particular, the price elasticities of demand in general equilibrium are not altered. This can be important for authors working with a previously calibrated model (e.g., see the paper by Beckman, Hertel and Tyner (2011) which incorporates outside estimates of the price elasticity of demand for energy). The AIDADS-AIDADS model entails more model modifications, and, most importantly in our view, may require additional model validation, depending on the application at hand. Unlike the CDE, the AIDADS specification does not lend itself so nicely to calibration to externally estimated price elasticities of demand. In short, the user can choose between these two options.

3. Processing Survey Information

Undertaking poverty analysis for a country using GTAP-POV requires a household survey for that country to identify its poor households, to estimate their prevalence, to understand where they earn their income in order to classify them by earnings strata, and to estimate the responsiveness of poverty headcounts to income changes in each stratum. As households with the greatest degree of earnings specialization are likely to be most affected by external shocks, we use the survey's earnings information to stratify households into different earnings specialization groups. This step in the analysis is the most complex as household surveys vary greatly in their coverage and detail. The present section of the paper discusses the steps required to extract the necessary information for parameterizing the poverty module for a given country. The procedures outlined here apply readily to the World Bank's Living Standard Measurement Study (LSMS) surveys but are general enough to be adapted to other sources of households earning information.

Three points should be borne in mind when choosing a country to be included in the poverty module. First, for rather obvious reasons it is highly desirable to choose a country which is already included in the GTAP database. Without explicit coverage of the country in question within GTAP, it is virtually impossible to implement a GTAP-POV analysis. Secondly, we suggest that the country should have a considerable percentage of population living below the poverty line in order

[13] The GTAP-POV application illustrated here (Hertel et al. 2009) is based on AIDADS-AIDADS specification. Readers interested in the CDE-AIDADS demand specification (Verma et al. 2011b) can obtain the model code from the authors.

to justify its inclusion in the GTAP poverty module. Poverty remains a policy problem in some of the richer countries in the world. However, the design of this poverty module is not well suited to addressing the likely impacts of trade reforms on poor households in wealthier industrial economies. Finally, the nationwide household survey must contain information on household income (wages and business income), as well as transfer payments, and a sufficient number of household characteristics to distinguish the nature of household members' employment and business enterprises.

The remainder of this section discusses how to process the survey, once a country has been identified and its survey obtained. Box 2 brings together in one place the key decision rules used throughout this exercise (these are largely drawn from Ivanic, 2004, which is an excellent reference for additional insights into this process). Figure 1 depicts where each step fits in the whole process. Both of these tools will be useful for the reader to have at hand as we move through the detailed procedures for processing the national survey. We classify all the sectors of economic activity listed in the survey as agricultural or non-agricultural (see Rule 1 in Box 2). Next, we must identify which are the poor households. To do so, we define a poverty line for classifying households as poor or non-poor (section 3.1). But before classifying the households as poor or non-poor, we classify them into various strata according to their income specialization (section 3.1.1). The stratum-specific, poverty headcounts are then used to calculate the national poverty headcounts and strata poverty shares in the national poverty (section 3.1.1). The next piece of information we need from the surveys is the poverty elasticity and section 3.2 describes the required steps. Finally section 3.3 tackles problems in deriving the earnings shares for the various strata. It starts out by mapping the 4 GTAP factors (labor – skilled and unskilled, capital and land) to the 10 sources of factor incomes (see Figure 2). Section 3.3.1 gives guidelines for determining earnings shares for the urban and rural wage labor strata, section 3.3.2 deals with the same for the agriculturally and non-agriculturally self-employed strata, section 3.3.3 touches on the transfer stratum while 3.3.4 mentions the urban and rural diversified strata.

Box 2: Guidelines for processing earnings data from the household surveys

Rule 1: *Sectoral Classification:* In order to map factor payments from GTAP to the poverty module, it is necessary to classify sectors of employment in the household survey as either agricultural or non-agricultural sectors. We classify all farming activities in the surveys as agricultural sectors. All the remaining economic activities are considered to be non-agricultural.

Rule 2: *Labor Skill Splits:* The GTAP database differentiates between endowments of *skilled and unskilled labor*. To make this differentiation in the household survey, we follow the GTAP definition (Liu et al. 1998) of skill levels which is based on occupational classifications. Skilled labor includes the work of managers and administrators (including farm managers), professionals and para-professionals. Unskilled labor is provided by tradespersons; clerks; salespersons and personal service workers; plant and machine operators, and drivers; laborers and related workers; farm workers and anything else which cannot be classified as skilled labor. *In the absence of occupational information* the skill level can be obtained by using education as proxy for occupation. Here, we assume that skilled labor is provided by individuals who have attended vocational school or college for some period of time.

Rule 3: *Total Reported wages* should include not just cash, but also the monetary equivalent of any in-kind remunerations received by household members in return for their labor in all paid employment. Wage earnings are commonly reported on a monthly basis but these time units could also be a day, week, fortnight, quarter or year etc. We calculate annual reported wages by multiplying the reported amount of time units (e.g., weeks) for which the job was held during a 12 month period by the remunerations received per time unit (in cash and in kind). In each case, one must employ the appropriate conversion factor to estimate annual earnings. *In the absence of information on time for which the job was held*, assume that individual was employed for entire year.

Rule 4: *Wages are imputed for each self-employed member of the household* and for the unpaid family labor engaged in the family business. Imputation is done by using the average reported wage rate for individuals who are not self-employed and have similar characteristics to the individual whose wage is being imputed. The set of characteristics considered typically includes region (typically rural or urban or in some instances the area –district or municipality – where the household is located), age, education and industry of employment. For example, one would impute the wage of an agriculturally self-employed skilled worker in region A by using the wage of a hired agricultural skilled worker in the same region, age category and with similar educational attainment. Some surveys might not provide an exact match for all characteristics of an individual and in those cases we try to get as close a match as possible for the self-employed individual whose wages are being imputed.

Rule 5: *Adjustment of imputed wages:* The imputed wages must be adjusted in cases where the sum of imputed skilled and unskilled wages exceeds the total reported business income (please see appendix 3 for a discussion on the imputation of business incomes, which are an essential component of the wage imputation process). The adjustment is applied to imputed wages in a proportionate fashion so as to ensure non-negative returns to capital. To calculate adjusted imputed agricultural wages first estimate the correction factor required to eliminate negative profits (γ_a):

$$\gamma_a = \frac{\overline{w}_{sa*} + \overline{w}_{ua*}}{b_a} \quad \text{if} \begin{Bmatrix} \overline{w}_{sa*} + \overline{w}_{ua*} > 0 \\ b_a > 0 \end{Bmatrix}, \text{ 0 otherwise}$$

Where $\overline{w}_{sa*}$ are the imputed skilled agricultural wages, $\overline{w}_{ua^*}$ are imputed unskilled agricultural wages, and b_a is the total reported profit from the household's agricultural enterprise. Corrected agricultural imputed wages are estimated as follows:

if $\gamma_a > 1$ $\quad \left\{ \overline{w}_{sa} = \dfrac{\overline{w}_{sa*}}{\gamma_a} \; ; \; \overline{w}_{ua} = \dfrac{\overline{w}_{ua*}}{\gamma_a} \right\}$

if $0 < \gamma_a \le 1$ $\quad \left\{ \overline{w}_{sa} = \overline{w}_{sa*} \; ; \; \overline{w}_{ua} = \overline{w}_{ua*} \right\}$

if $\gamma_a = 0$ $\quad \left\{ \overline{w}_{sa} = \overline{w}_{ua} = 0 \right\}$

Similarly, non-agricultural wages are corrected as follows:

$$\gamma_{na} = \frac{\overline{w}_{sna*} + \overline{w}_{una*}}{b_n} \quad \text{if} \begin{Bmatrix} \overline{w}_{sna*} + \overline{w}_{una*} > 0 \\ b_n > 0 \end{Bmatrix}, \text{ 0 otherwise}$$

where $\overline{w}_{sna*}$ are imputed skilled non-agricultural wages, $\overline{w}_{una*}$ are imputed unskilled non-agricultural wages and b_n is the total reported profit from the household's non-agricultural enterprise. Then, corrected non-agricultural wages are estimated as follows.

if $\gamma_{na} > 1$ $\quad \left\{ \overline{w}_{sa} = \dfrac{\overline{w}_{sna*}}{\gamma_{na}} \; ; \; \overline{w}_{ua} = \dfrac{\overline{w}_{una*}}{\gamma_{na}} \right\}$

if $0 < \gamma_{na} \le 1$ $\quad \left\{ \overline{w}_{sna} = \overline{w}_{sna*} \; ; \; \overline{w}_{una} = \overline{w}_{una*} \right\}$

if $\gamma_{na} = 0$ $\quad \left\{ \overline{w}_{sna} = \overline{w}_{una} = 0 \right\}$

Rule 6: *Imputing returns to land and capital:* Since household surveys do not report returns to land and capital directly, these must also be inferred based on enterprise profits, wages paid and imputed wages. The logic is as follows: Total profits are assumed to represent payments to land, labor and capital. Once we have deducted wages and imputed returns to labor from profits, we are left with the sum of payments to land and capital. In the case of non-agricultural enterprises, there is no distinction made between payments to land and capital; both are treated as nonagricultural capital. So all the non-agricultural business income left after deducting the imputed skilled and unskilled wages or self-employed labor is attributable to capital in the sector.

In the case of agricultural enterprises, we must separately apportion payments to agricultural capital and agricultural land, as their factor returns are differentially affected by (e.g.) trade reforms in the GTAP model. Of course, those individuals constructing the GTAP data base face the same problem when apportioning value-added between land, labor and capital. The GTAP data base solves this problem by drawing on econometric studies of agricultural costs (Hertel et al. 2008) which typically utilize time series national data to estimate the share of costs attributable to each factor of production. Here, we use the GTAP estimate of the share of land in total non-labor value-added in agriculture, in order to partition these factors.

The formula used is as follows:

$$c_l = \max\left(0, \alpha\left(b_a - \overline{w}_a\right)\right)$$

where c_l is the factor return to land, α is the GTAP determined land share of aggregated agricultural capital and labor (note that α would be different for different regions), b_a is the reported profit from the household own agricultural enterprise, and $\overline{w}_a$ are the imputed wages for household members working in the agricultural unit. The remainder is naturally apportioned to capital as follows, adding in any additional rental income:

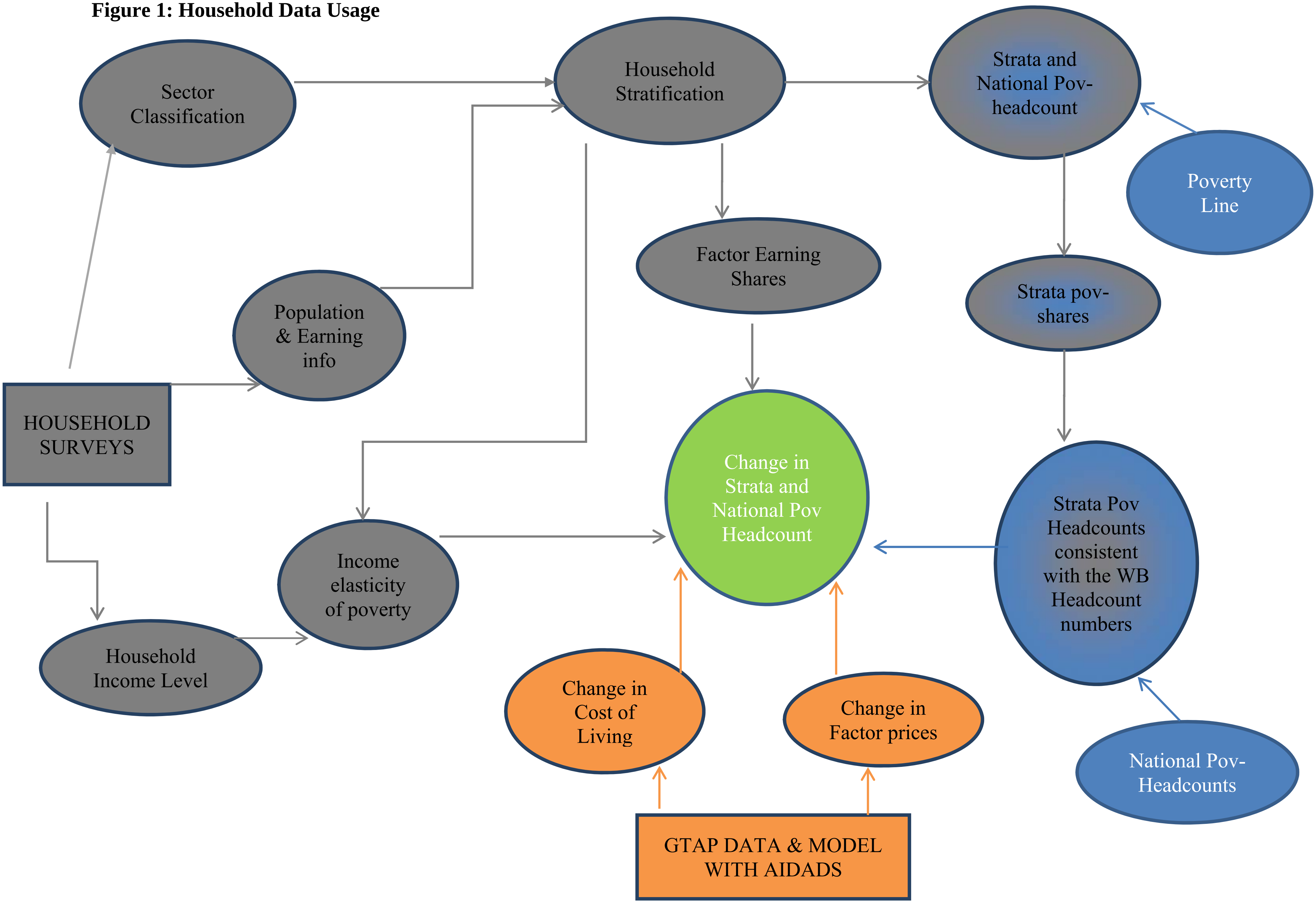
$$c_a = \max\left(0, \left(1 - \alpha\right)\left(b_a - \overline{w}_a\right)\right) + r_a$$

where c_a is the factor return to capital in agriculture and r_a is the reported rent income from agricultural property - cash and in kind payments received for renting out any land and/or agricultural equipment (in-kind payments should be valued at the average market price in the region).

Rule 7: Transfer income refers to cash, and in-kind transfers from the government and private entities to the household. These include, but are not limited to, social insurance, social subsidies, scholarships, pensions for orphans or widows and, different sources of assistance (NGOs, government and church), gifts and remittances from friends and family, both at home and overseas. In-kind payments should be valued at the average market price in the region (e.g., for wheat) to impute the value of in kind payments.

Note that the guidelines provided here are not exhaustive and some surveys might pose additional problems that are not illustrated here. Researchers will have to resolve those on the basis of standard household survey procedures. We encourage you to communicate with the authors of this Technical Paper so that future revisions can take account of these additional contingencies.

Figure 1: Household Data Usage



3.1. Poverty Headcount and the Choice of Poverty Line

In order to measure the poverty headcount, we need to first define a poverty line. There is a vast literature on this topic, and we do not attempt to review the associated controversies here. From the point of view of GTAP-POV, the most important thing is comparability across countries. If we were to use national poverty lines, it would be very difficult to generalize findings. For example, is the poverty impact of a WTO agreement more modest in country X due to the nature of its economy, or is this due to the fact that its national poverty line is much higher than in countries Y and Z? For this reason we adopt the World Bank's estimated poverty lines, which have been designed to facilitate comparability across countries, and for which poverty headcounts are regularly updated.

Earlier work with GTAP-POV adopted the World Bank's '$1/day' extreme poverty measure. In order to permit comparability with this earlier work we recommend that authors continue to evaluate their household survey data around this poverty line. However, this extreme poverty line has recently been updated to $1.25/day (Ravallion et al. 2009). Future contributors must work with this poverty line, at a minimum, in order to qualify for inclusion in GTAP-POV. In addition, it is useful to add the same calculations for the $2/day international poverty line, as well as the national poverty line. Indeed, once work is underway, it is not difficult to produce poverty module parameters for several poverty lines, and this is strongly encouraged. The marginal cost of adding another poverty line at the beginning is quite small and the GTAP-POV code has been written in a manner which permits the inclusion of multiple poverty lines. This permits authors to report both the change in poverty, as measured by both international as well as a national metrics.

Since incomes in the household survey are reported in local currency units, and the international poverty lines are in international purchasing power parity dollars, it is not immediately obvious how the two should be combined. The approach chosen here is to focus on the officially reported poverty headcount based on international (or national) poverty lines and use that to determine where the poverty line falls in the survey-based income distribution. For example, consider the case where the World Bank reports that 30% of the population in a given country falls below the $1/day poverty line. We then "line everyone up from poorest to richest" in the survey, and obtain the survey-based income distribution by applying survey sampling weights to individuals in these households. We then draw a line through this estimated income distribution such that 30% of the country's population lies below this line. The marginal household (i.e. the household falling at this line) defines the poverty level of income for purposes of processing the survey. In this way *we are able to indirectly infer the international poverty line in local currency units*, without having to worry about the exchange rate issues. Appendix 1 provides an example of how to find the poverty line using Stata.

3.1.1. Strata Level Poverty Headcount

For the sake of convenience, it is useful to repeat the poverty headcount expression (6) from the theory section above to clarify the type of information which must be extracted from the household survey. Firstly, it is clear that, before going further, we must stratify households by earnings specialization: s.

$$\widehat{H}_r = -\sum_s \beta_{rs} \cdot \varepsilon_{rs} \cdot \sum_j \alpha^p_{rsj}\left(\widehat{w}^m_{rj} - \hat{y}_r\right) + \varepsilon_r \cdot \widehat{T}_r + \varepsilon_r(\hat{C}^p_r - \hat{y}_r) \qquad (12).$$

Within each of these strata we will need to separately identify the poor households, using the poverty line(s) established in the previous section. Therefore, we must next classify all the survey households into strata depending on how they derive majority of their factor income.

Stratifying the Households:

Households in GTAP-POV are grouped into seven different strata on the basis of information about three different aspects of their earnings: (1) their sector of occupation (agricultural or non-agricultural), (2) whether the household members are self-employed or work for wages, and (3) their location of residence (rural or urban). If a household is engaged in multiple economic activities, the household surveys also report how much of their income they get from each activity, so one can also calculate the percentage of income coming from each source. Once we have all this information, we can allocate them across the strata as follows:

a) All households with more than 95% income from self-employment belong to either the "*agricultural self-employed*" or the "*non-agricultural self-employed*" stratum, depending on whether their income comes from the agricultural or non-agricultural sectors (as identified by Rule 1 in Box 2).

b) Households receiving more than 95% of their income from wage labor are classified as belonging to either the "*rural wage labor stratum*" or the "*urban wage labor stratum*" depending on the household's location, *irrespective of their sector of employment*.

c) Households receiving more than 95% of their income from transfer payments are assigned to the "*Transfer-dependent*" *stratum*.

d) All others[14] are grouped in two categories – "*urban diversified*" and "*rural diversified*" – strata, depending on their location of residence (urban or rural).

Stratifying the Households when information is missing:

As indicated above, the stratification of households depends on three essential pieces of information: sector of occupation, the nature of the individual's employment and the location of the household. When these three components are present, stratification is reduced a procedural manner. However, often one or more of these components is missing. Below we outline some of the issues and potential remedies that can emerge during the stratification process.

The first potential issue arises from the absence of information on the sector of occupation. Some surveys do not directly report whether the individual is employed in agriculture or not. To address this issue, it is necessary to look carefully into the description of the economic sector of the business, company or institutions where the individual works to determine if that individual is in the agricultural sector or not. If this information is not available, other sources of information

[14] These strata also include households for which the information required to correctly stratify them is missing.

can often be found in surveys. For Jamaica for example, we have used the description of the workplace (e.g. construction site, shop, plantation, farm, garden) recorded in the survey to assign the sector. Once the workers employed in the agricultural sector are identified, all other workers can be categorized as non-agricultural. Most surveys record information for primary occupation and secondary occupation, which means that the sector of occupation may need to be identified twice depending on whether the individual has one or two occupations[15]. Lastly, forestry and sometimes fisheries are included in agriculture when the sector of occupation is reported and no information is available to separate forestry and fishery from agriculture.

The second issue that may arise is the absence of information on whether the individual is self-employed or a wage worker. When this information is not provided, secondary variables usually offer clues to help in identification. The most obvious way to identify is if the survey separates wage income from business income. If so, then even if individuals are not specifically tagged as self-employed or waged, the analyst can easily tag him/her by looking at the source of income. Complete absence of information on the status of the individual's work is rare. Not so rare, however, is for this information to be missing for the secondary occupation of the individual. If data exist on the primary occupation of the individual, say for instance self-employed, but are missing for the secondary occupation (and no secondary variables exist to help) then we have generally assumed that the secondary occupation was as a wage worker. This assumption is based on the fact that an individual is unlikely to have two wage jobs at the same time. It is possible that the individual has two different businesses, but we do not allow for this possibility here.

Some individuals are tagged as "non-remunerated" workers in the survey. The premise required to deal with these individuals is that a household member can work for the family business and not be formally remunerated. If correct, this premise implies two things: (i) the individual is self-employed if the household reports and business income; and (ii) A wage can be imputed for this individual (see section 3.3.2.2).

Missing information on whether the household is rural or urban is the third potential issue in the process of stratification. Recent work with Latin American countries has led us to proceed as follows to resolve this issue. Households with individuals working in agriculture were assumed to be in the rural area. Once these individuals are identified, the locational characteristics of their households, particularly sub-regions, municipalities or departments, can be used to construct a location identifier for agricultural households. This identifier allows us to impute the rural location to households with the same identifier. Implicit in the construction of the identifier is that the more disaggregated the location is, the more accurate the identifier and therefore the imputation will be. Households that were not identified in this process were assumed to be urban. Problems arise when datasets for certain countries present geographical identifiers that are too broad such as state or provinces. In such cases, allocating the sector (urban or rural) to an entire state becomes a more ambitious assumption, whose appropriateness may vary from country to county.

[15] A number of different variations can exist in relation to the way countries report income. For Venezuela, for instance, total and primary occupation incomes were reported. Income from secondary occupation could be derived from the two variables provided. However, because the type of occupation (waged or self-employed) was only provided for the primary occupation, obtaining the income from the secondary occupation would not be useful, as it would not be possible to allocate it properly.

Calculating Stratum Poverty Headcounts:

After grouping all the households into the seven strata listed above; we calculate the stratum poverty headcount in the same fashion as was done for the population at large. First, sort agents belonging to a stratum by their per capita income, from lowest to highest. Apply the survey sampling weights to each household to obtain an estimate of the full population stratum income distribution and as described in section 3.1. (Note that this might require splitting the weight associated with a representative agent to arrive at the correct aggregation.) Then, using the poverty line defined in terms of local currency units obtained above, work out the stratum poverty headcount by summing over the individuals with per capita incomes equal to or less than the poverty level of income. The result provides an estimate of the number of people in country r who earn less than the poverty level of income and belong to a given stratum s: (H_{rs}). The sum of these stratum poverty headcounts must equal the national poverty headcount obtained previously: ($H_r = \sum_s H_{rs}$). Furthermore, we can also obtain the stratum poverty shares used in (6) as follows: $\beta_{sr} = \frac{H_{sr}}{H_r}$, where, by construction $\sum_s \beta_{sr} = 1$ for all r.[16]

Estimated stratum shares in poverty by country and region:

We have applied this stratification methodology to household surveys from 31 countries and the results are reported in Table 2. Countries are grouped by region, beginning with Sub-Saharan Africa, then continuing to Asia, and finally to Latin America and the Caribbean where our most recent work has been undertaken. Within each region, countries are ordered by per capita income (PPP basis). The poverty line used in these exercises has been the lowest measured international poverty level – hence the term 'absolute poverty'. This corresponded to \$1/day in the surveys prior to the year 2000. Subsequently we have used the more recent, \$1.25/day definition of absolute poverty to define the cut-off when processing the household surveys.

Comparing poverty patterns across the three regions, we generally see a larger share of absolute poverty in households earning virtually all of their income from agriculture. Poor households in Asia tend to have more diversified income sources. And the same is true in the LAC region. As one moves from poorest to richest country/years within each region, there is a tendency for the relative share of agriculture-specialized households in absolute poverty to diminish, while urban poverty's contribution rises. This parallels the structural transformation that typically accompanies economic development. Overall, the most striking feature in this table is the tremendous heterogeneity in poverty patterns around the world.

[16] When survey and GTAP-POV data have different base years, one can take the estimated poverty shares and apply them to a new total poverty headcount (corresponding to the GTAP-POV base year). In doing so it is assumed that the composition of poverty has not changed between the survey base year and the benchmark year for GTAP-POV.

Table 2. Share of absolute poverty in the seven different earnings strata

Region	Country	Year	Strata						
			Agric	NAgric	Urban Labor	Rural Labor	Transfer	Urban divrs	Rural divrs
Sub-Saharan Africa									
	Mozambique	1998	0.41	0.13	0.01	0.05	0.14	0.06	0.19
	Malawi	1998	0.54	0.11	0.00	0.03	0.07	0.01	0.25
	Uganda	1999	0.09	0.04	0.00	0.03	0.02	0.07	0.75
	Tanzania	2000	0.23	0.02	0.30	0.05	0.28	0.01	0.11
	Zambia	1999	0.34	0.23	0.10	0.07	0.07	0.09	0.11
Asia									
	Bangladesh	1996	0.15	0.13	0.04	0.22	0.03	0.07	0.37
	Cambodia	2004	0.19	0.07	0.11	0.14	0.29	0.08	0.13
	Vietnam	1998	0.04	0.11	0.00	0.00	0.05	0.10	0.70
	Laos	2003	0.16	0.11	0.10	0.12	0.35	0.08	0.08
	Pakistan	1998	0.02	0.07	0.05	0.15	0.28	0.43	0.00
	Philippines	1999	0.11	0.06	0.03	0.05	0.03	0.23	0.49
	Indonesia	1993	0.42	0.12	0.02	0.07	0.04	0.06	0.28
	Thailand	1996	0.06	0.02	0.00	0.06	0.11	0.07	0.68
Latin America-Caribbean									
	Nicaragua	2010	0.19	0.17	0.02	0.08	0.02	0.12	0.40
	Honduras	2010	0.08	0.06	0.02	0.03	0.10	0.15	0.54
	Bolivia	2007	0.49	0.10	0.02	0.01	0.01	0.05	0.33
	Paraguay	2010	0.36	0.06	0.03	0.02	0.01	0.16	0.36
	Guatemala	2011	0.15	0.05	0.02	0.04	0.07	0.19	0.48
	Dominican Rep	2004	0.11	0.08	0.02	0.03	0.05	0.34	0.37
	El Salvador	2010	0.14	0.08	0.04	0.13	0.01	0.13	0.46
	Ecuador	2005	0.28	0.05	0.01	0.01	0.00	0.17	0.48
	Jamaica	2010	0.07	0.38	0.15	0.15	0.00	0.07	0.18
	Peru	2010	0.31	0.03	0.01	0.00	0.00	0.24	0.41
	Colombia	2010	0.10	0.14	0.01	0.09	0.03	0.19	0.45
	Costa Rica	2010	0.06	0.05	0.07	0.21	0.02	0.23	0.36
	Uruguay	2006	0.09	0.09	0.00	0.00	0.18	0.45	0.18
	Panama	2009	0.06	0.05	0.01	0.01	0.19	0.12	0.57
	Brazil	2011	0.01	0.01	0.02	0.01	0.01	0.76	0.18
	Chile	2009	0.00	0.00	0.02	0.03	0.31	0.42	0.22
	Mexico	2012	0.09	0.03	0.03	0.09	0.14	0.21	0.42
	Venezuela	2011	0.08	0.29	0.11	0.04	0.08	0.34	0.06

Note: Within regions, countries are ordered from poorest to richest based on base year per capita income. Poverty lines are $1/day for the surveys pre-dating the year 2000 and $1.25/day thereafter.

3.2. Poverty Elasticity

As is clear from (6), predicting poverty headcount changes in the wake of a given policy shock requires us to estimate of income elasticity of poverty for each stratum in order to infer the poverty headcount changes implied by the income changes at the poverty line in the stratum. As shown in (1) above, this elasticity is the slope of the cumulative distribution function of the poverty headcount, evaluated at poverty level of income. This section discusses how to estimate this elasticity, which we define as the ratio of the proportionate change in poverty headcount to the proportionate change in income.

Based on experience to date, we find that focusing on a grouping of 10 percent of the stratum population around the poverty line works well. Picking just a few households can result in extreme results (e.g., very large elasticities, or elasticities of zero). Accordingly, we take 10/2 = 5 percent of the total stratum population on each side of the poverty line. In cases where 10 percent of stratum population translates into a number greater than the poverty headcount in the stratum, we restrict the number of households to be twice the number of poor households in the stratum. We then use this particular decile of the stratum population in order to compute the poverty elasticity. This is done by computing the cumulative poverty headcount at the two end points of the stratum sub-section, converting this to a proportionate change, and then dividing by the proportionate change in per capita income between these two end points. The resulting ratio is our estimate of ε_{rs} in (6).

In some cases, the calculation of elasticities may require additional steps, particularly in cases where the resulting elasticities are very sensitive to the selection of the household (immediately above or below the specified quintile). The difference in per-capita income between consecutive households (sorted in ascending order) can be a cause of concern if the differences are too large and may impact elasticities in a significant way. In such cases, smoothing techniques can be used to minimize the impacts of such large variations in income. Our work for El Salvador serves as a good example. By using a local polynomial to smooth out per-capita incomes, the national elasticity for El Salvador dropped from 2.98 to 2.5 at the $1.25-a-day poverty line. We have found that local polynomial smoothers work well with household data in general, but the best specification of the regression[17] varies from country to country. This means that the selection of bandwidth or kernel for the regression will largely depend on how the data are presented and on plots done to assess which smoother best fits the data. The calculation of elasticities as well as the smoothing of incomes is discussed in detail in Appendix 2 which also offers the commands and the procedures required to automate the elasticity calculation even in the presence of zero incomes.

So far we have identified the poverty headcounts, poverty shares and poverty elasticities, as well as the aggregated poverty elasticity: $\sum_s \beta_{rs} \cdot \varepsilon_{rs} = \varepsilon_r$. It remains to estimate the earnings shares at the poverty line.

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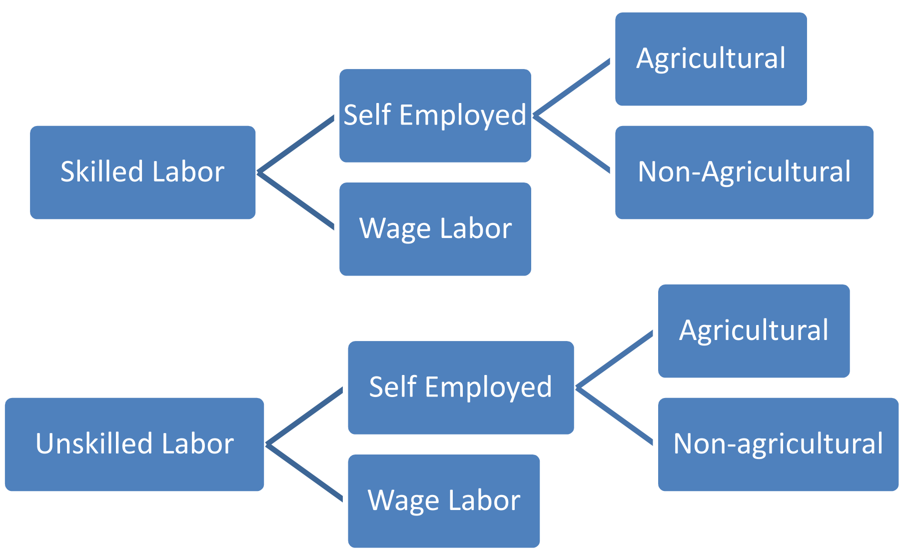
[17] The reader is encouraged to read the presentation of this technique in the Stata documentation available at http://www.stata.com/manuals13/rlpoly.pdf. This document describes not only the econometric underpinnings of the *lpoly* command but also discusses how to find the best fit for the data.

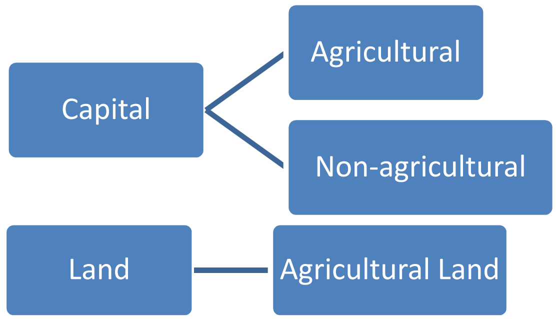
3.3. Obtaining Factor Earning Shares from Household Data

Now we come to the most demanding part of the exercise: estimating earnings shares at the poverty line for each stratum: α_{rsj}^{p}. From equation (6) it is clear why these shares are so important. Consider a household deriving 70 percent of its income from unskilled agricultural wages; when unskilled agricultural wages rise by 10%, household's real income rises by 7% (holding all other factor returns and commodity prices constant). This 10% unskilled agricultural wage rise will have a very different impact on poverty for this household than would be the case for a household earning just 5 percent of its income from unskilled agricultural wages, which would experience just a 0.5% real income rise.

To assist us in this process, we have summarized in Box 2 the key rules used in allocating households earnings data to particular earnings categories. The goal here is to obtain the closest possible mapping from the GTAP model to the household survey. Of course, in the standard GTAP model, labor and capital are perfectly mobile across sectors, so it doesn't matter which sector a factor is employed in. The return to this mobile factor will be the same, regardless of the sector, and will change at the same rate across all uses. However, this runs counter to empirical evidence in most developing countries where significant wage differences exist for workers of similar skills – particularly between agriculture and the non-farm sectors. As a consequence, special purpose versions of the GTAP model, with more limited mobility have been developed. As noted above, GTAP-POV draws inspiration from the GTAP-AGR model which incorporates estimates of factor mobility across agriculture and non-agriculture as described previously so that returns to (e.g.) farm capital, can diverge from non-farm capital. Therefore it matters whether a household's capital earnings are derived from farming or non-farming enterprises.

Figure 2. GTAP Factors and Household Survey-based Income Sources





Here we briefly outline the structure of GTAP-AGR factors and sectors which, in turn, guide us in how we should process the survey information to be consistent with this classification. Figure 2 identifies the five main factors of production in the GTAP model: Land, Skilled Labor, Unskilled Labor, Capital and Natural Resources[18]. Land is used in Agricultural sectors only[19], so this is really 'farmland'. Skilled labor, unskilled labor and capital are used in both Agricultural and Non-agricultural sectors, and returns in the two sectors are linked through factor mobility equations. Since inter-sectoral mobility is imperfect, these returns can diverge, and they tend to do so when the agriculture and non-agriculture sectors are differentially affected by a given policy reform.

From the point of view of the household surveys, labor (both skilled and unskilled) may participate in the wage labor market and/or it may be self-employed. The surveys typically do not identify the sector in which wage labor is employed. Therefore, we simply refer to this as wage labor and map its returns to the average economy-wide wage for skilled or unskilled labor. In the case of self-employed labor, the household receive a sector-specific wage, depending on whether it is employed in agriculture or non-agriculture.

Unfortunately, we have no information about returns to natural resources (largely fossil fuels and mining) in the household surveys, so this source of factor earnings is ignored in the poverty analysis. To the extent that these resource rents accrue largely to foreign companies, government enterprises, and high income households, this omission will not be serious for purposes of poverty analysis.

There are 57 sectors in the GTAP model, of which the first 12 refer to primary agricultural activity. These are the 'agricultural sectors' referred to in Rule 1 of Box 2. In some cases, authors might wish to adopt a broader definition which would include agriculture, fishing and forestry – the first 14 sectors in the GTAP data base. In this case, the factor market segmentation in GTAP-POV must be changed to encompass this group of 14 sectors so that the definitions of agriculture are consistent between the GTAP-POV model and the approach used to process the household survey.

Building on Figure 2, Table 3 lists the 10 sources of household income encompassed in GTAP-POV. It furthermore links them to the household strata for which they predominate. By

[18] Natural resources are deemed to be a residual claimant on factor earnings and are thus subsumed in capital earnings (or land in the case of agriculture).
[19] Non-farm land is not a separate factor but is a part of non-agricultural capital.

assumption, with 95% of household income coming from farming in the Agriculture Self-employed stratum, agricultural self-employment labor income, agricultural capital and land returns dominate there. Similarly for the Non-agriculture Self-employed stratum, which earns 95% of household income from sector-specific earnings in the non-farm sector. Wage labor households receive 95% or more of their incomes from wage labor, so that establishes their primary income sources. And transfer dependent households obtain virtually all of their income from public or private transfers, which are indexed to net national income for reasons discussed previously. This leaves urban and rural diversified households, which, by definition, obtain their incomes from a variety of sources.

Table 3. Strata and Associated Earning Factors Specialization

Stratum	Major Earning Factors
Agric (Agriculturally Self-employed)	1. Agriculturally Self-employed Skilled Labor 2. Agriculturally Self-employed Unskilled Labor 3. Agricultural Capital 4. Land
Nagric (Non-agriculturally Self-employed)	1. Non-agriculturally Self-employed Skilled Labor 2. Non-agriculturally Self-employed Unskilled Labor 3. Non-agricultural Capital
Ulabor (Urban Wage Labor)	1. Skilled Wage Labor 2. Unskilled Wage Labor
Rlabor (Rural Wage Labor)	1. Skilled Wage Labor 2. Unskilled Wage Labor
Transfer (Transfers)	1. Transfers
Udivrs (Urban Diversified)*	-
Rdivrs (Rural Diversified)*	-

* by definition being diversified means that neither wage labor nor business income or transfers account for more than 95 percent of reported income of the household belonging to these strata.

We now turn to a discussion of how to allocate survey-reported household income for each stratum to these major earning factors. Having listed the guidelines in Box 2, we frequently refer to the applicable rules in that box throughout the following sub-sections.

3.3.1. Urban and Rural Wage Labor Strata

These two strata comprise households that derive most of their income from the sale of their own wage labor. Rule 2 discusses how to determine if the labor should be classified as skilled or unskilled. Note that a given household may well supply both skilled and unskilled labor if members are engaged in different types of jobs.

3.3.1.1. Labor: Determining Skill Levels

There is some debate in the labor economics literature regarding how best to identify skilled labor. One approach is based on the individual's human capital – typically proxied by educational attainment. This has the advantage of being clear-cut, but the fact is that some CEOs have minimal education, while college graduates often take low-skill jobs in the service sector. In other words, skilled labor (e.g., management) is not always highly educated – particularly in rapidly developing, low income economies. The alternative approach is to base this distinction on occupation by observing what the individual actually does. This is the preferred approach in GTAP (see Rule 2). However, in the absence of data on occupation, we revert to the education-based measure. Note that if there is no information on wages, then they must be imputed following the methods described below.

3.3.1.2. Labor: Calculating *Total* Reported Wages

Rule 3 specifies how the survey information on total reported wages is processed. Keep in mind that the information on *total reported wages* is used as a reference to impute wages of self-employed individuals with similar characteristics (details to follow in subsection 3.3.2.2).

Table 4. Reported wages in the sample

household ID	member ID	cash wage job 1 (monetary value)	cash wage job 1 (frequency)	In kind wage job 1 (monetary value)	In kind wage job 1 (frequency)	cash wage job 2 (monetary value)	cash wage job 2 (frequency)
1	1	150	month	15	month	20	week
1	2	15	week	5	biweekly	150	annual
2	1	25	daily	100	annual	-	-
2	2	500	annual	-	-	10	daily
2	3	30	quarterly	5	weekly	50	annual

Member 1 of household 2 isn't employed in job 2 and member 2 doesn't receive any in kind remunerations.

The total annual reported wage for household 1 is 4,080 from which 3,020 are earned by member 1 and 1,060 are earned by member 2. Earnings of each individual member are calculated[20] as

Annual Reported Wages = (cash wage job 1)*(conversion factor) + (in kind wage job 1)*(conversion factor) + (cash wage job 2)*(conversion factor)

member 1 wages =150*12+15*12+20*52 = 3,020

member 2 wages = 15*52+5*26+150*1 = 1,060

Note that this procedure applies to calculating wages for both skilled and unskilled labor in both rural and urban wage labor strata. Also for either of the strata these two types of reported wages should exhaust more than 95 percent of the households' reported wages, as these are specialized strata. The remaining income (less than 5 percent, by definition) must be attributed to the other eight sources of factor income in this framework. If any member of household belonging to urban or rural wage labor strata is self-employed, then some of the income will be allocated to the self-employed labor (skilled/unskilled in agricultural/non-agricultural self-employment, whichever the case may be). Similarly if the household owns property or farm-land and rents it out then those factors too should be accounted for in the household income. These types of imputations

[20] Note the assumption that the individual was employed during the entire year given the unavailability of information on the length of employment.

are discussed below where we consider the cases of households for which such earnings sources comprise the majority of their income.

3.3.2. Agricultural and Non-agricultural Self-employed Strata

Income reported by the agricultural self-employed households is taken to be reported agricultural business income. The self-employed household's income is expected to be a composite of wages to family labor (skilled as well as unskilled), payments to land and to agricultural capital/equipment (here we exclude rents received on land/equipment rented out; these will be added back later, to determine total returns to land/agricultural capital). To know the earning shares we need to divide this business income into components attributable to each of the four factors (For surveys where agricultural business income is not reported, it can be calculated as value of agricultural production net of input expenditures and payments to hired labor). Similarly for non-agriculturally self-employed households, the business income can be seen as coming from family owned labor (skilled and unskilled) and non-agricultural capital owned by household. Remaining income (beyond business income) must be apportioned to the remaining earnings factors listed in Table 3.

3.3.2.1. Labor: Determining Skill Levels

By following the guidelines in subsection 3.3.1.1 we can identify if the type of family labor provided by the self-employed household should be considered skilled or unskilled. There are, however, difficulties associated with defining skill levels, particularly when the range of professions and educational degrees is large. For instance, in Peru the list of qualifications covers over 5,000 codes and various sub-categories of professions. Thus, within the skilled workers there are varying degrees of specialization. This suggests that a very large group of workers may be qualified as skilled but their skills range broadly. Future work may look into further disaggregating levels of skill. For example, a salesperson can be a fruit vendor or a computer salesman. Similarly, secretary can be executive, legal, medical or simply clerical. Next we need to impute the wages for the self-employed labor.

3.3.2.2. Labor: Imputing Wages

We follow Rule 4 to impute wages for self-employed labor or family labor as well as for cases where there is missing wage information. We also need to verify the presence of business incomes for all households that have self-employed members. If the business income is missing, it needs to be imputed (see Appendix 3 for a discussion of how to do so). The rules apply to both skilled and unskilled types of labor. An example will help to illustrate the approach. Consider the data on *average reported wages across all income sources* provided in Table 5. An individual residing in region 1, who is 20 years old, with a third grade level of educational attainment and is employed in industry 2, receives an annual monetary compensation of 400 (this includes both cash and in kind earnings, see subsection 3.3.1.2. above).

Table 5. Average reported wages

Row Observation	Region	Age	Education	Industry	Average Reported Wage (monetary value/year)
1	1	20	3	2	400
2	1	35	4	4	500
3	1	44	2	1	200
4	1	50	5	3	700
5	2	17	1	1	150
6	2	39	3	4	395
7	2	60	5	2	754
8	3	27	5	5	370
Average					433.6

Now consider Table 6, which presents a list of self-employed individuals, along with information on their characteristics.

Table 6. Self-employed individuals information

ID	Region	Age	Education	Industry
14	1	35	4	4
25	2	50	5	3
43	3	40	3	4
52	4	50	1	5
55	4	55	0	6

We want to impute annual[21] wages for the individuals listed in Table 5. In this process, we will encounter a variety of special cases as noted below. The general rule of thumb for this exercise is to find the best possible match (highest number of characteristics match) for individuals in Table 6 from individuals in Table 5 and if more than one such matches exist then use the average of those reported wages to calculate imputed wages as reported in the final column of Table 7.

Case 1: Exact match for every characteristic for individuals in Table 5 and Table 6

ID 14 = average (region=1, age=35, education=4, industry=4)
= average reported wage for Observation 2 in Table 5
= 500

Case 2: Some characteristics match those of individuals in Table 5

ID 25 = average (region=2, age=50, education=5, industry=3)
(There is not an exact match under Table 5 for this individual; however observation 4 provides the best match with 3 of the 4 characteristics identical)
= average reported wage for Observation 4 in Table 5

[21] When information on the length of time employed on that particular job is available, multiply the corresponding average annual reported wage by the appropriate conversion factor; otherwise, assume the individual was employed during the entire year.

= 700

ID 43 = average (region=3, age=40, education=3, industry=4)
(No exact match again but Observation 6 under Table 5 is the best approximation with 2 identical characteristics)

= average reported wage for Observation 6 in Table 5
= 395

ID 52 = average (region=4, age=50, education=1, industry=5)
(No exact match but Observation 8 under Table 5 is the best approximation as it matches the industry of employment, we consider the industry of employment a closer determinant of wages relative to the other characteristics considered in this exercise, which are, in order of preference, education, region and age.)

= average reported wage for Observation 8 in Table 5
= 370

Case 3: No characteristics match any of the cases in Table 5
ID 55 = average (region=4, age=55, education=0, industry=6)
(As none of these characteristics match those of any individual's in Table 5 so we take a simple average over the entire sample in Table 5)

= 433.6

Finally, since the imputed wages sometimes exceed the total business income, Rule 5 specifies how to adjust the reported income.

Table 7. Imputed wages for the self-employed

ID	Region	Age	Education	Industry	Imputed Wage (monetary value/year)
14	1	35	4	4	500
25	2	50	5	3	700
43	3	40	3	4	395
52	4	50	1	5	370
55	4	55	0	6	433.6

Performing the imputation on household datasets which often contain thousands of observations requires a systematic procedure that can be automated. There are a variety of software packages that can perform the imputation in a way that correctly imputes the wages. In Appendix 4, we illustrate one possibility of automating the process using Stata.

3.3.2.3. Returns to Capital and Land

After netting out the imputed wages to self-employed family labor, the remaining business income is apportioned to capital and land. In the case of non-agricultural sectors in GTAP-POV, land is not a factor of production and so all income represents capital earnings. In the case of agricultural business income, it must be apportioned to farmland and agricultural capital. At this point, we should add to this any payments received by the self-employed household for renting out land and agricultural equipment owned by the household. The estimate thus arrived at is then split between land and capital returns using the GTAP shares as described in Rule 6.

In cases where a household reports simultaneous income from agricultural and non-agricultural household-owned businesses, we proceed as follows: First, label accounting profits by the industrial classifications (ISIC version 3 or 4) as either agricultural or non-agricultural. Next associate household members with each of these incomes based on the type of job they report in the labor module of the survey, and subtract their imputed wages from the business proceeds to obtain returns from these businesses. When the contribution of individual household members to each type of the business is unclear or when a single person runs an agricultural and a non-agricultural business at the same time, we attribute labor income based on the relative sizes of these businesses. This means, for example, that when a single person with imputed income of 75 currency units reports agricultural sales of 100 and non-agricultural sales of 200, we assume he or she contributed 25 (=75*100/300) units of labor to the agricultural business and the rest to the non-agricultural business.

The returns to land and capital may present additional difficulties in their calculation, particularly the returns to capital. This is because most surveys do not specify whether rental income is from agriculture or not. In some cases, it is possible to allocate the income to agriculture if the business is in agriculture and if the items contained in the rental data are related to agriculture (for instance, tractor rentals, or rentals of other agricultural equipment). However, in other cases the description of what is included in the rental income data is far from clear and often combines agricultural and non-agricultural components. As a result, the decision to include such data becomes entirely subjective. For the work done in Latin America, we have generally opted for the conservative route and did not include rental income if it was ambiguous in nature.

3.3.3. Transfers

Rule 7 in Box 2 describes how to handle transfer payments.

3.3.3.1 Remittances

Remittances were introduced as a component of the earning shares with the new wave of Latin American countries. Remittances can be seen as a special kind of transfer, one which involves individuals sending money or in-kind payments to other individuals (as opposed to governments or organizations). The degree to which countries report remittances varies considerably. Both within country and overseas remittances have to be considered. Sometimes, overseas remittances are reported in Euro, US$ or other currencies and require the appropriate exchange rates to convert the data to local currency units.

3.3.4. Urban and Rural Diversified

Recall that there are two types of households included in these two strata – a) Households for which complete information is available and neither wage employment nor self-employment income accounts for over 95 percent of income – hence the term 'diversified' and b) Households where income information is not available. For the first type we calculate the returns to self-employed and wage labor (skilled and unskilled) using the guidelines already outlined above. They simply exhibit more diversification of sources than do the specialized households.

For the second type of households we simply apply the economy wide average skilled and unskilled wage rates for individuals with similar characteristics. We can classify whether the labor is skilled or unskilled just as we did for the other strata (Rule 2).

Once we have distributed reported income across all ten earnings categories, the ratio of each factor's return to total income of household gives us the factor earnings share for the household. To get an equivalent number for the entire stratum, we simply compute an average over all households in the stratum.

4. An illustration: Poverty impacts of a WTO Agreement

Given the substantial effort involved in generating a poverty-extended version of the GTAP model, it is legitimate to ask: Is this worthwhile? The answer to that question will depend on the application undertaken. If the goal is simply to inform decision making related to domestic policy in a single country, then the researcher is likely better off using a more flexible, single-country framework. However, if the goal is to analyze international poverty impacts of global change, then we believe this framework can have great value. We have previously provided a list of the published applications (Box 1) that have been undertaken using this framework. This section outlines in detail the application for which GTAP-POV was originally developed, namely assessing the poverty impacts of multilateral trade reform.

There are a whole series of papers using variants of the theory laid out above in order to assess the poverty impacts of trade reforms. In Hertel et al. 2004, the authors simulate the poverty module independently of the GTAP model, so prices are passed from the CGE model to the poverty simulation model. The poverty model is then solved for households across the entire income distribution (at the level of twenty vigntiles). This ambitious exercise was valuable, and certainly preferable to focusing solely on households in the neighborhood of the poverty line. However, it has several drawbacks that make it undesirable in the context of this Technical Paper. Firstly, it is much more costly in terms of time and computing resources. The poverty module was implemented in GAMS, so that the pass-off of prices from one model to the other involved translation from one software package to another. More importantly, the construction of the underlying data set was much more demanding, as it involved characterizing earnings across the entire income distribution. An attempt was also made to reconcile the earnings data reported in GTAP and in the household survey data. This proved very challenging, and is described in detail in Ivanic (2004). The second problem that arises with this approach to poverty modeling is that it can be very difficult to interpret/explain results. The authors found that in order to explain the results, they needed to develop the kind of equations outlined in section 2 of this paper. This led to the question: Why not simply embed these equations directly in the CGE model, thereby circumventing the complexity of working with multiple models/software packages and allowing for more direct economic analysis? When combined with the AnalyseGE feature of GEMPACK (Pearson et al. 2002), this greatly facilitates the delivery of new insights and sophisticated analysis of the poverty impacts of trade reforms. In short, GTAP-POV sacrifices computational complexity (and completeness of distributional analysis) for ease of analysis and insights.

As noted in the introduction to the technical paper, if one is just interested in the impacts on poverty in a single country, it is far more satisfying to utilize a single country CGE model with many disaggregated households and richer institutional detail pertinent to the country in question (e.g., Ferriera-Filho and Horridge 2006). The methodology for linking such a single country model to multi-region GTAP is developed in detail by Horridge and Zhai 2006. However, concluding that the WTO's Doha Development Agenda (DDA) was not as poverty friendly as the elements excluded from that package – for Brazil alone – would not have carried the same weight. It would be easy to suggest that Brazil was an exception. To support such a broad statement, there is a need to consider a wide range of countries from different regions of the world, with different patterns of poverty. Hence the use of GTAP-POV for this question.

In our opinion, the most important finding to emerge from the application of GTAP-POV to the analysis of multilateral trade liberalization is that reported in the Hertel et al. 2009. These authors conclude their analysis of the poverty impacts of the DDA with the following statement: "The DDA, as proposed, is less poverty friendly than the trade reforms which are left out of this proposal." They explain why this is the case: the problem is that the most poverty friendly reforms come in the form of tariff cuts on food and agricultural products in the developing countries. (This lowers food prices for the poor, who spend a large share of their income on food.) Yet the design of the DDA proposal – in particular the idea of allowing the least developed countries to have a 'free pass' on trade reforms – ended up leaving these reforms out of the package. Meanwhile, the pieces of the DDA which received the most attention – reductions in domestic support and export subsidies for agriculture in the rich countries – were the least poverty friendly aspects of the DDA. In short, the entire exercise was misguided given the overall goal of this 'Development Round" of the WTO! How was the GTAP-POV framework used to reach such a striking conclusion? We now review the authors' findings.

Hertel et al. 2009 choose the GTAP version 6.1 data base (Dimaranan 2006) as their starting point for this general equilibrium analysis of the DDA. Though other versions are usable, the choice is determined by the fact that virtually all analyses of the Doha Development Agenda started with the same data set. Data availability is easily the most limiting resource for global analysis of trade reforms. For their scenarios, the authors draw on the carefully constructed Doha reform scenarios developed and utilized in the books edited by Anderson and Martin 2006, and Hertel and Winters 2006. Included in the Doha reform scenarios are the necessary experiments for updating key trade policies to 2005, thereby establishing that year as the benchmark policy year for trade liberalization experiments.

In order to better understand which policies are driving the poverty changes, the authors focus first on the poor country poverty impacts of rich countries liberalizing agricultural policies in isolation and then contrast it with agricultural trade reforms in the poor countries themselves. Finally, they bring in non-agricultural reforms (in both rich and poor countries) to complete the global reform scenarios. In terms of depth of reforms, they consider both full liberalization (a natural benchmark, but highly unlikely politically) as well as a Doha scenario derived from the July 2004 Framework Agreement (WTO 2004). The Doha scenario follows the core liberalization assumptions in Hertel and Winters 2006 and is summarized alongside other policy scenarios (see Box 3) of the (longer) working paper version of Hertel et al. 2009.

Box 3: Elements of the DDA Scenario Based on the July Framework Agreement

Agriculture:
Market access—use nonlinear (tiered) formula (as with progressive income tax):

For developed countries, marginal rates (45, 70, and 75 percent) change at 10 and 90 percent tariffs

For developing countries, marginal rates (35, 40, 50, and 60 percent) change at 20, 60, and 120 percent tariffs

For LDCs, no cuts to tariffs

AMS: apply tiered formula:

For developed countries, marginal rates of 60 percent (AMS less than 20 percent) and 75 percent

For developing countries, marginal rate of 40 percent

For LDCs, no cuts to domestic subsidies

Export subsidies abolished

Non-agriculture:
Market Access: 50 percent cuts in tariffs (33 percent developing countries, 0 percent LDCs).

Owing to the significant challenges in summarizing the detailed findings across a range of countries, the authors propose the following method; they claim that what we really want to know are answers to the following questions: (a) do the reforms raise or lower poverty? And (b) is the impact of a given reform on the sample of poverty countries large in magnitude? To answer these questions for their sample of countries, the authors compute the following measures for each variable of interest: the Average Value (AV), Average Absolute Value (AAV) and the Sign Consistency (SC) measures. These are defined as follows: AV is the simple average of the percent changes in the concerned variable for all countries, AAV reports the average magnitude of the percent change in the same, irrespective of its direction, and SC = AV/AAV depicts how much the direction of changes in these drivers' differs across countries. If the policy in question raises poverty in all regions, for example, then AV = AAV and SC = 1. Similarly if it lowers poverty in all regions, then AV = - AAV and SC = -1. In general, SC falls between these extremes and offers a measure of the tendency of a policy to be poverty increasing or poverty reducing.

Table 8 reports the poverty impacts (percentage change in the $1/day headcount) across the sample of countries assembled by Hertel et al. 2009, for this GTAP-POV application. Using the GEMPACK 'subtotal' feature (Harrison, Horridge and Pearson, 1999), the authors are able to decompose the poverty changes with respect to various components of the full reform package, including rich, poor and combined agricultural reforms, non-agricultural reforms, and full liberalization. The impact of DDA reforms are also reported in the lower panel of this table for purposes of contrast. And the AV, AAV and SC measures across the entire sample are reported in the bottom rows of the panels both for full liberalization and for the DDA partial reforms. Note that the numbers in table are percentage changes in poverty headcounts which can be calculated using the absolute changes in poverty headcounts (model simulation results for variable *c_REGHDCNT*) and initial poverty headcount numbers (header *HDCT* in basedata.har).

Consider first the impact of agricultural liberalization in both rich and poor countries (Combined Agric Reforms) under the Full Liberalization scenario. Here we see that only Mexico and Venezuela would see an increase in the poverty headcount. Furthermore, the AAV summary measure of 1.91 indicates significant movement of persons across the poverty line due to agricultural reforms. Indeed, comparing this to the AAV for rich country and poor country agricultural reforms individually, we note that the magnitude of poverty impacts from combined rich and poor country reforms is significantly more important than either one implemented alone. The sign consistency value of -0.93 is also higher for the combined reforms than the either of the two sets of reforms alone and indicates that global agricultural trade reforms are heavily weighted in the direction of poverty alleviation. This outcome is a direct consequence of the fact that both developed and developing country reforms reduce poverty – but each tends to do so for a different segment of the population. Rich country agricultural reforms tend to benefit the rural poor, while poor country agricultural reforms tend to benefit the urban poor. Thus, their poverty benefits are complementary in nature.

The bottom panel in Table 8 reports the corresponding results from the Doha Reforms. With the partial reforms only 7 of the 15 countries realize a reduction in the poverty headcount as against 13 under Full Liberalization. The limited poverty reduction impact is reflected in the small value for the AAV of 0.31 for agricultural reforms shown in the bottom of the lower panel of Table 7. Also, the lack of uniform cross-country reductions of these partial reforms is reflected in the more moderate sign consistency value (-0.76), which is considerably smaller than that under full agriculture reforms (-0.93).

The fourth column of Table 8 reports the focus country poverty impacts of non-agricultural reforms and the fifth column show the same effect combined with agricultural reforms (full liberalization and Doha, respectively). As seen in the fourth column the full reform of non-agricultural tariffs contributes to a poverty increase in the majority of our focus countries. However, the AAV of 0.80 is less than the values for full agricultural reforms in either the rich or poor countries, indicating a lesser absolute impact on poverty, and the sign consistency of 0.22 indicates a mixture of poverty increases and decreases (note the importance of the large reduction in Vietnam in this calculation). In the bottom panel of Table 8, these same impacts are reported for Doha reforms in non-agriculture and we see that the AAV is smaller (0.13 versus 0.80), indicating less impact, but slightly more consistent in sign (SC = 0.32), indicating that the impact of the Doha reforms across this sample countries is somewhat more consistently poverty raising than is the full reform package.

The final column in Table 8 reports the combined impact of all merchandise trade reforms on poverty in our focus countries. The full reforms reduce poverty in 9 of the 15 countries, with a Sign Consistency of -0.81 and an average absolute value of 1.96. On the other hand, Doha reforms (last column in lower panel) reduce poverty in only 7 of the 15 countries, with lower Sign Consistency and an AAV only about one-fifth as large. Thus, the authors conclude that the Doha reforms only generate about one-fifth of the poverty change generated under Full reforms and are considerably less poverty friendly. This stems from the fact that both the agriculture and the non-agriculture Doha reforms are individually less poverty friendly than the full reforms.

From this, we believe it is clearly demonstrated that the application of GTAP-POV in the context of a large number of countries can permit researchers interested in the poverty impacts of global policies to reach important conclusions. This is greatly facilitated by the use of these simple, summary measures (AV, AAV and SC). In their 2009 paper, Hertel et al. also compute these summary measures for the fundamental drivers of poverty changes, as discussed in section 2 of this paper, above. These include: factor earnings and the cost of living at the poverty at the poverty line, as well as any tax changes required to offset forgone tariff revenue. Overall, GTAP-POV appears to be a useful framework for multi-region, multi-country poverty analysis.

Table 8. Percentage change in the $1/day Head Count under Agr and Nonagr Reforms

Country	Rich Agric. Reforms	Poor Agric. Reforms	Combined Agric. Reforms	Combined Non-Agric. Reforms	Total
	Full Liberalization				
Bangladesh	-0.11	-0.18	-0.29	0.57	0.29
Brazil	-1.79	-0.15	-1.94	0.52	-1.42
Chile	-3.89	-1.41	-5.30	0.31	-4.99
Colombia	-0.29	-0.28	-0.57	0.67	0.10
Indonesia	-1.24	-0.82	-2.06	0.61	-1.45
Malawi	-0.74	-0.96	-1.70	-0.14	-1.84
Mexico	0.31	0.61	0.92	0.43	1.35
Mozambique	0.07	-1.08	-1.01	0.32	-0.69
Peru	-0.40	-0.23	-0.63	-0.16	-0.80
Philippines	-0.76	-0.56	-1.32	0.57	-0.76
Thailand	-6.63	-4.55	-11.18	2.31	-8.87
Uganda	0.04	-0.06	-0.02	0.08	0.07
Venezuela	0.26	-0.15	0.11	0.75	0.85
Vietnam	0.22	-1.70	-1.48	-4.38	-5.85
Zambia	0.14	-0.29	-0.16	0.24	0.09
Average	-0.99	-0.79	-1.78	0.18	-1.59
AAV	1.13	0.87	1.91	0.80	1.96
Sign Cons.	-0.88	-0.91	-0.93	0.22	-0.81
	Doha Reforms				
Bangladesh	0.00	-0.01	-0.02	-0.03	-0.05
Brazil	-0.72	-0.04	-0.76	-0.04	-0.79
Chile	-0.99	-0.30	-1.29	0.00	-1.28
Colombia	-0.17	0.01	-0.15	0.06	-0.09
Indonesia	-0.13	0.07	-0.06	-0.14	-0.20
Malawi	0.41	-0.06	0.35	0.00	0.35
Mexico	0.15	-0.13	0.02	0.11	0.13
Mozambique	0.05	-0.05	0.00	0.02	0.02
Peru	0.04	0.00	0.04	0.02	0.06
Philippines	0.02	0.00	0.02	-0.27	-0.25
Thailand	-1.42	-0.35	-1.77	-0.20	-1.97
Uganda	0.04	0.00	0.04	0.00	0.04
Venezuela	0.12	-0.05	0.06	0.14	0.21
Vietnam	0.14	-0.21	-0.07	0.96	0.89
Zambia	0.03	-0.01	0.02	0.01	0.03
Average	-0.16	-0.08	-0.24	0.04	-0.19
AAV	0.30	0.09	0.31	0.13	0.42
Sign Cons.	-0.55	-0.86	-0.76	0.32	-0.46

Source: Adapted from Hertel et al. 2009.

5. Summary and Future Directions

In summary, the GTAP-POV framework offers a relatively simple vehicle for beginning to assess the broad-based, international poverty impacts of a wide range of global policies. As pointed out previously in this paper, this framework is not a substitute for detailed, single country modeling of poverty impacts of policies. By virtue of their restricted geographical scope, such studies are much better suited to incorporating richer data sets and more complete characterizations of the mechanisms contributing to changes in poverty in a given country. However, as shown in section 4, there is clearly a role for GTAP-POV assessments when it comes to global trade policies, and likely also in the case of other global shocks, such as climate change.

As regards, the current state of GTAP-POV, there is much to be done to make this framework more useful and permit it to be more widely used. The first order of business is to extend and update the country coverage. A natural target for future contributors is the benchmark year for the next GTAP release. Given the fact that GTAP-POV utilizes the household survey data in elasticity and share form (e.g., share of a given stratum's income coming from unskilled agricultural labor), it should be acceptable to use surveys which fall within a few years of the benchmark period. In principle, we recommend going for the most recent year, as this will render them policy relevant for a longer period of time.

We have largely side-stepped the deeper issue of reconciling the household survey data with the GTAP data base. We cite the work of Ivanic (2004) on this issue and note that this is a major challenge. By way of example, he finds that the household income surveys typically underreport income from capital by a very large amount. In order to reconcile the two data bases, some households must be allocated a great deal more income. Depending on how this allocation is done, there can be a sharp change in the income distribution and/or the poverty headcount. In short, such reconciliation exercises go far beyond the realm of GTAP and its extensions. Nonetheless, future work in this area would be most welcome.

Looking ahead, we hope that, with the publication of this paper, along with our offer to produce a GTAP-POV version of the model for any authors successfully contributing a new poverty data set, it will be possible to build momentum for a vastly expanded set of poverty countries. We draw encouragement from GTAP Technical Paper No. 1 (Huff, McDougall and Walmsley 2000) which has become a roadmap for contributors of national input-output tables to the GTAP data base. While the v.1 GTAP data base had just 12 IO tables embedded in it, the v.9 data base included more than ten times that many regions! This dramatic expansion is a tribute to the power of networks. We hope that the publication of this GTAP Technical Paper will contribute to similar momentum for the GTAP-POV model.

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Appendix 1: Finding the poverty line in Stata

In Stata, these this operation can be achieved with the following commands:

1.*sort incper*
2.*cumul incper [aw=expr] , gen(pctcheck)*
3.*sort pctcheck incper*
4.*gen poor=1 if incper<=728,400*
where ”incper” is the per-capita income and “expr” is the expansion factor.

Command 1 sorts the per-capita income. The second command generates the empirical cumulative distribution of the per-capita income and stores it in a variable named “pctcheck”.

Both per-capita income and the cumulative distribution variable are sorted in order to facilitate finding the poverty line. For Chile for example, the income that corresponds to the national poverty line of 15.1% in 2009 was 728,400 pesos. The poor and non-poor can then be defined using that poverty line (command 4).

A similar procedure is applied to uncover the other poverty lines. Poverty headcount ratio data are provided by the World Bank via its World Development Indicators portal. Ideally, the information on the poverty line should be for the same year as the survey year. In the absence of data for the same year, the year that most closely matches the survey’s year should be used.

Appendix 2: Polynomial smoother

As indicated in the text, incomes can be smoothed using a local polynomial smoother (*lpoly* command in Stata), or any other method that best suits your data. The syntax of the *lpoly* requires two variables y and x. y is the variable to be smoothed and x is the regressor or the variable that will be used to "guide" the smoothing process. Options (after the comma) include the kernel choice and the bandwidth:

lpoly income sequence, kernel(gaussian) bwidth(0.3) degree(2) generate(abs incper)

Also in the option list is the command "*generate*" which requires two variables: one to store the grid of the smoothing procedure (e.g. *abs*) and one that stores the smoothed point estimate.
Once incomes are smoothed, we can apply calculate the elasticities.

gen ela1q=. /*generates a variable that will identify households around the poverty line*/
foreach i in 1 2 3 4 5 7{ /*loops across all strata, note that stratum 6 is missing because the first observation is equal to zero. We deal with that below*/
sort incper lag`i' /*sorts per-capita income and the cumulative income shares for each stratum/*
summ lag`i' if strata==`i' & poorst==1, det /*obtains relevant parameters for the elasticity*/
replace ela1q=1 if lag`i'>=`r(max)'-0.05 & lag`i'!=. & lag`i'<`r(max)'+0.05 & strata==`i'
/*replaces ela1q=1 for households around the poverty line */
}

"*poorst*" is a dummy variable indicating if a given household is poor (*poorst=1*) or not within each strata.

For stratum six, we can proceed as below to find the first non-zero household.

sort incper lag6
summ lag6 if incper!=0 & strata==6 & poorst==1
local ab=r(max)-r(min)
dis `ab'
summ lag6 if strata==6 & poorst==1, det
replace ela1q=1 if lag6>=`r(max)'-`ab' & lag6!=. & lag6<`r(max)'+0.05 & strata==6

Below is the actual elasticity calculation, which follows the technical paper

sort strata incper poorst
gen cumstrata1q=poorst
by strata: replace cumstrata1q=cumstrata1q + cumstrata1q[_n-1] if _n>1 /*generates a cumulative count of the poor around the poverty line */
sort strata ela1q incper

Generating elasticities

gen elasticity1q=.
gen numerator1q=.
gen denominator1q=.

by strata ela1q: replace numerator1q=(cumstrata1q[_N]-cumstrata1q[1])/cumstrata1q[1] if poorst==1 /*calculates the proportionate change in the number of poor around the poverty line*/
by strata ela1q: replace denominator1q=(incper[_N]-incper[1])/incper[1] /*calculates the proportionate change in per capita income around the poverty line*/
replace elasticity1q=numerator1q/denominator1q /*divides the numerator by the denominator */
label var elasticity1q "stata level elasticity at $1.25 a day" /*generate a label */
bysort strata: egen strataeloneq=mean(elasticity1q)
label var strataeloneq "mean elasticity by strata at $1.25 a day"

Calculating a weighted elasticity that will be used to obtain the national poverty line. First, estimate the share of poor within each stratum and for the relevant poverty line.
egen natpoor1q=total(poor) if poor!=0
where "*poor*" is a dummy variable indicating if a given household is poor (*poor=1*) or at the national level.

Within strata count
bysort strata: egen stratpoor1q=total(poorst) if poorst!=0
gen povsharest1q=stratpoor1q/natpoor1q
label var povsharest "share of strata poor to total poor"
*gen agelast1q=povsharest1q*elasticity1q*
label var agelast1q "weighted strata level elasticity at $1.25 a day"

Appendix 3: Imputing business income

Implicit in the concept of wage imputation, as described in this paper, is the assumption that business incomes are reported for all households that have self-employed workers. This, however, is not the case for a number of countries. In some datasets, some households may not contain or report business incomes even when at least one member of the household is self-employed. Thus, business income needs to be imputed for these households. The procedure to impute business income follows the same logic as the wage imputation, but instead of using characteristics of the workers (education, age, etc.), business characteristics are used instead (location, type of business, number of employees).

The process of imputation of business incomes is not free of issues. There are three distinct types of Problems which arise:

1. The household has more than one self-employed individual working in the same sector (say, agriculture) and they have the same business characteristics: the imputation of business takes into account characteristics of the business and looks for similar characteristics in households that have business incomes. If there is more than one individual in the household but the business characteristics are the same, the business income will be imputed more than once. Because the business income is constructed at the household level, meaning that the reference business incomes are at the household level, we need to ensure that when business incomes are imputed only one individual reports the imputed business income. Thus, corrections need to be made to avoid double counting.

2. The household has more than one self-employed individual working in the same sector (say, agriculture) and they have different business characteristics: slight variations in the business characteristics will translate into differences in the imputed business incomes. Thus, if there are more than one self-employed individual, more than one business income will be imputed. While it is possible that the household has two businesses in the same sector, we have generally found that the total amount of business incomes that results from adding up the imputations are too large to be credible. Therefore, we have opted to choose the highest business income among the members of the household and apply that for the household.

3. The household has more than one self-employed individuals working in different sectors: when the sectors vary, we need to assume that the household has more than one business and, as a result, two business incomes. Corrections in this scenario apply only if there is more than one self-employed individual in each of the sectors.

Appendix 4: Imputing wages using Stata

The secret to coding the imputation of wages is to realize that combinations of particular traits (e.g. education, age, location) can be grouped and coded into numbers. Below we show an example:

Status	Age *(years)*	Location *(state)*	Education *(levels)*	Sector	Grouping
Wage	21	TX	3	18	1
Self-employed	22	AK	5	5	2
Self-employed	32	FL	2	10	3
Self-employed	21	TX	3	18	1

We note from the table above that individuals with same characteristics (age, location, sector, and education) have the same grouping regardless of their status. This occurs because the grouping reflects the combination of traits and is unique to individuals with specific characteristics. Stata has a function, appropriately called group, which allows the user to perform the grouping quickly. Once the grouping has been made, we can search for waged-individuals of the same group as self-employed and apply their average income to the self-employed individuals. Given the large number of possible combinations, we need to apply this process using a loop, as demonstrated below.

Starting with the greatest number of traits:

gen inc_busprim=. /*creates a variable that will hold the imputed wages */

egen idtag=group(regional age education profession skill) if profession!=. /* generates the grouping based on region, age, profession, and skill level*/

qui levelsof idtag if (selfempprim==2 | selfempsec==2) & wage_inc!=. & wage_inc!=0, loc(bla) clean /*identifies individuals that are wage-based within each group and have non-missing and non-zero wages and store these individuals into a macro, called bla (could be called anything); variables "*selfempprim*" and "*selfempsec*" indicate if an individual is self-employed or a wage worker in the primary and secondary occupation*/

set more off

foreach k in `bla' { /*loops across every individual in the macro bla/*

qui summ wage_inc if idtag==`k' /*obtains the average wage of waged-workers for every group*/

replace inc_busprim=`r(mean)' if idtag==`k' & inc_busprim==. & selfempprim==1 /*replaces the variable that was generated in the beginning with the average wage for each group if the individual is self-employed, belongs to the group and has a missing imputed wage. */

}

This process is then repeated using fewer variables to generate the groups so that more individuals can have imputed wages. In our experience, we have had to run the loop three or four times for most countries in order to cover most individuals. Note that this process has to be done for both primary and secondary incomes.