Findings and Conclusions

Main Findings

Poverty refers to deprivation of certain essential goods and services. It is a multidimensional concept, covering not only income but also other equally important non-income aspects, since two households having the same per capita income might have different welfare levels because of their differences in the non-income aspects. The overarching goal of the Asian Development Bank (ADB) is poverty reduction. Given the current poverty situation in Asia and the Pacific, the challenge ahead is daunting. The latest indicators, for instance, show that developing member countries (DMCs) of the ADB seem to be moving toward achieving MDG No. 1 of halving poverty by 2015. This, however, means that the poverty incidence rate would still be around 17 percent in 2015 as the starting point of the rate in 1990 was about 34 percent. Fortunately, serious concern over poverty reduction among various stakeholders outside ADB is also evident. This is reflected, among other ways, in the Millennium Development Goals (MDGs) and in the increasing number of pro-poor programs by various institutions. In this context, poverty impact analysis (PIA), in addition to other impact assessments, is very important in ensuring that programs reach the right beneficiaries.

This book deals with impact assessment issues, particularly on developing tools and providing examples of their applications. The main contributions of the book are in the areas of identifying the poor, mapping poverty, and performing impact analysis using CGE modeling frameworks.

Poverty Impact Analysis

PIA aims at bringing about better allocation of resources—a goal that has become increasingly important for developing countries, where resources are scarce. PIA essentially examines a project or program to see whether it has generated its intended effects on the targeted group. Findings from a PIA provide critical feedback for officers and policy makers to help them better design and implement ongoing as well as future programs. PIA results can help project officers be more accountable to the donor community and general public, especially regarding the relevance and management of the project.

Each PIA design is unique—it depends on many factors such as the project's main purpose, data availability, local capacity, budget constraints, and time frame. Two important aspects of PIA include: identifying the poor and measuring the project impact on the poor. The latter can be conducted by developing the right counterfactual such as in the computable general equilibrium (CGE) modeling framework.

Development and Application of the PIA Tools

The Economics and Research Department of ADB has conducted a series of research studies to develop tools for a PIA that maximizes the use of available information and techniques for the different stages in PIA. There are five different tools discussed in this book:

- poverty predictor modeling (PPM) for identifying the poor at the household level;
- poverty mapping for identifying the poor over geographical areas;
- CGE modeling for assessing the economy-wide effects and distributional implications of wide-ranging issues on the economy with representative household groups (RHGs);
- CGE-microsimulation modeling for conducting assessments such as in CGE modeling but with a complete household data set; and
- poverty reduction integrated simulation model (PRISM), which is essentially an integration of CGE-microsimulation modeling and poverty mapping using a geographic information system (GIS) application in a dynamic, interactive, and user-friendly way.

The identification of the poor is very important since they are the main beneficiaries of pro-poor programs. At the household or individual level, this can be conducted through PPM by relying on household attributes or poverty determinant variables.

PPM provides a practical alternative to the time-consuming and expensive way of collecting data on income and expenditure for assessing poverty at the local levels. With PPM, the poverty predictor variables can be transformed into a short questionnaire for a quick survey to replace the long questionnaire of household income and expenditure surveys. The quick survey was pilot tested in the People's Republic of China (PRC), Indonesia, and Viet Nam.

In addition, there are other ways of assessing the poor such as by using independent assessments from respondents, enumerators, neighbors, and village chiefs to determine the poverty status of respondents. The use of these assessments was also explored in the pilot surveys to provide alternative and more participative ways of classifying the poor that can complement the result based on the household income and expenditure survey.

Identifying the poor over specific regions or areas was conducted through poverty mapping. The technique basically maximized the rich information of surveys and the wider coverage area of censuses to estimate reliable poverty indicators for more disaggregated geographical areas. The estimation was based on the modeling relationship between poverty indicators and some common variables available in both surveys and censuses. The results were then "mapped" on census data to get estimates of poverty indicators for a wider coverage area.

The next aspect of PIA, identification and measurement of the impact, can be conducted by using quantitative or qualitative methods, or both, including developing a counterfactual to minimize selection and other biases. On the measurement issue, PIA measures could include a broader concept of poverty measures beyond the general poverty measures, such as headcount ratio, poverty gap, and poverty severity. In some cases, other poverty or well-being indicators might be more relevant since many pro-poor programs do not necessarily directly target the poor household, instead they work through increasing employment or improving access to various services such as education, health, and sanitation.

In the economy-wide context, a CGE modeling framework can provide "with" and "without" scenarios, and therefore provide a solid counterfactual. This approach also provides information about the impact transmission mechanism, detailing how the intervention affects different workers, households, and markets in the economy. The poverty impact in the CGE context, however, can only be examined at the RHG level. To examine poverty impact at the household level, the CGE modeling is linked to a household data set in the CGE-microsimulation modeling. Furthermore, in the PRISM, the CGE-microsimulation model is linked to a GIS application in a user-friendly way to make the spatial dimensions of the PIA interactive and easy to use.

Identifying Poor Households

Household income or consumption data for a particular area are not easy to gather. Household surveys to collect such data are costly and based on samples, which may not be representative of the particular area concerned. Hence, there is a need for identifying poor households in the area targeted for policy intervention or impact analysis. The methods used for predicting the household poverty status based on easily collected and verifiable household attributes are the consumption correlate model, logit/probit model, and principle components analysis. All three methods were implemented for Indonesia, the first two for the PRC, and the first for Viet Nam.

The first method predicts per capita consumption expenditure using predictor variables that are highly correlated with it; such as possession of land and other durable assets, household demographics, education level, occupation, house type and size, and access to services. The predicted consumption expenditure can then be used for determining household poverty status. The second method also uses similar predictors, but the dependent variable has binary values of *1* and *0* representing poor or not. In the third method, an asset index is constructed following Filmer and Pritchett (1998a) by pulling out a few linear combinations that best capture the common information from a large number of variables. Even though they referred to the bottom 40 percent of households in the asset index as poor, they did not intend to use the asset index for a poverty measure. However, given that household assets are closely correlated with income or consumption, it is natural to use this variable as a proxy indicator for arranging households on a poverty scale. For classifying poor and nonpoor, the authors use a cutoff point below which the proportion of the poor would be the same as that obtained directly from consumption survey data.[1]

The survey-based evidence shows that the predictors do serve the purpose, for they are able to identify most of the poor. The studies also included perceptions of respondents, local officials, and enumerators that tally predominantly with the poverty ratio. Perception analysis is based on direct questions on whether a household could be regarded as poor or not and the answer would normally be in reference to a local standard that is not necessarily the same across all respondents. Therefore, the results could be more a measure of relative poverty than absolute poverty since subjective judgments are involved.

On the similarity of perception results of respondents, local officials, and enumerators, the enumerators might have played a key role in explaining the poverty concept. Notwithstanding the possibility of subjectivity, the fact that results tally closely with those based on consumption criteria implies that properly trained enumerators could by and large identify poor households. This obviously serves a verification purpose. Perception of the poor is important for both identifying the poor and for impact assessment.

1 A simple but similar alternative is to assign scores for various household assets and identify poor households if they get a total score below a critical level. This approach is adopted in India for identifying below–poverty line households for several government interventions. A similar procedure is also applied in Indonesia to classify poor people based on 14 predictor variables in the latest census of poor people targeted for the fuel subsidy program.

It is important to know what the poor conceive as poverty, their ability to overcome it, and the opportunities and risks they foresee.[2]

Indonesia. The three methods to predict poverty were implemented by using the National Socioeconomic Survey (Susenas) data set. The results show that the consumption correlates model is the best approach, predicting poverty correctly for more than 60 percent of respondents in urban and rural areas. Prediction for rural areas is 52.7 percent accurate, while prediction for urban areas is 49.6 percent accurate.

The rough guide to predicting poverty in Indonesia would be based on information about asset ownership, education level, and consumption pattern. Variables that correlate with poverty, either negatively or positively, are: ownership of car and refrigerator, education level, household size, and consumption of milk and beef. The roles of household characteristics such as employment status of household members and access to facilities in explaining poverty are relatively small but significant.

Results from the validation survey show that the effectiveness of poverty predictors for rural, urban, and total, are 83.4 percent, 86.6 percent, and 77.3 percent, respectively. The numbers demonstrate a high accuracy of predicting the poor. The shares of nonpoor households predicted as poor in rural and urban areas, are only 9.9 percent and 7.4 percent, respectively, while poor households predicted as nonpoor in both areas are 6.7 percent and 6.1 percent, respectively.

If the results of applying different methods of independent assessment or perception are also used, i.e., by concentrating only on the group of respondents having consistent poverty status based on expenditure survey and independent assessment, the effectiveness of prediction increases to 93.1 percent, 82.2 percent, and 91.0 percent, respectively, for rural, urban, and total.

The People's Republic of China. Poverty predictors based on easy-to-collect individual, household, and community variables in the PRC were estimated using multiple regression and logit models. The estimation used data from the PRC's Rural Poverty Monitoring Survey. The results show that both models can accurately predict the poor by over 50 percent. The significant predictor variables include household characteristics such as productive age (15–60 years old) of family members, household composition, and number

2 A poverty reduction policy involving credit, for instance, must consider willingness of the poor to take risks in building new small enterprises by borrowing to improve their conditions. Such participatory methods could be extended to impact assessment through focus group discussions.

of school age children. Also important are the characteristics of household head, such as gender, age, and education level. Other important predictors are household possession of a telephone, truck, TV set, livestock, or large grain storage. Land resources, difficulty in collecting fuels, participation in insurance programs, use of gas or coal for cooking, a big event taking place within the year, and participation in community activities are also important variables in predicting poverty. From the community variables, households living in villages designated as poor villages or encountering natural disasters and having less access to roads, tend to have low per capita consumption.

The validation survey results show that the poor are correctly predicted by more than 80 percent. The prediction uses a logit model and CNY1,500 as the poverty threshold. In general, households having low income or facing limited access to income sources tend to be poor. As the predictors were initially derived by correlating the household's per capita consumption expenditure and the household's characteristics, these predictors reflect the relevance of purchasing power as a factor in defining poverty. In addition, because the predictors were also derived using local perceptions of poverty, they likewise could, in principle, encompass the multidimensional aspects of poverty that include not only the level of income but also other "local" factors that make a household socially and economically disadvantaged.

Viet Nam. The development of PPM in Viet Nam was conducted in four stages:

- examining the relationship between poverty and household characteristics using a multiple regression model and data from the 2002 living standards survey;
- testing the significant predictors using 1998 data to examine the consistency and stability of the models across time;
- implementing the same modeling procedure in two provinces of the North Central Coast to further test the methodology and to examine whether poverty predictors may be different at a more disaggregated level; and
- generating poverty predictors and a short questionnaire for high-frequency implementation of data collection at the local level.

Overall, PPM in Viet Nam performs well across different data sets. The predictor variables include ownership of assets (such as TVs and motorbikes), demographic characteristics (number of dependents and working family members, education status), and housing conditions.

Poverty Mapping

Poverty estimates at national or provincial levels are commonly available from household income or expenditure surveys. Sample size and distribution normally do not permit estimates at a smaller administrative or geographical level with adequate precision. This makes the poverty indicators less useful for poverty reduction programs with a small coverage area. Following the small-area estimation technique developed by Rao (1993), Elbers, Lanjouw, and Lanjouw (2003a) developed and applied a poverty mapping method to estimate poverty indicators for small areas. This method has now been applied in many countries. The technique maximizes the rich information of surveys and the wider coverage area of censuses by developing a regression model to estimate income or consumption based on common independent variables available in the household survey and census, and predicting poverty indicators for smaller areas based on applying the regression to census data. This census-survey matching method is to fill the gap in dealing with small-area poverty estimates such as for districts or even smaller administrative areas.

Poverty mapping has shown to produce reliable poverty estimates for areas consisting of as few as 15,000 households. Such estimates are obviously very helpful for resource allocation in poverty reduction programs, for impact analysis of welfare programs, and for monitoring. The technique's use could be broadened to other areas such as access to education or health service. [3]

The poverty mapping in Indonesia used data sets of the 1999 SUSENAS, 2000 Population Census, and 2000 Village Census. The results show that reliable poverty indicators can be generated at the subdistrict level with standard errors of estimates at less then 10 percent. At the village level, however, the standard errors increase to nearly 14 percent, making the estimates less reliable.

An interactive and dynamic GIS application of the poverty mapping results is then developed to enhance the spatial aspects of poverty analysis. The GIS application is to display spatial poverty characteristics as well as to visualize meaningful relationships between poverty indicators and other poverty-related data. The tool for doing this is called Poverty Related Information System for Monitoring and Analysis or, simply, PRISMA.

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3 A 2006 World Bank research evaluation has, however, questioned the accuracy of poverty mapping estimates since these estimates may be biased due to the presence of spatial correlations. Thus, it would be prudent to use poverty mapping results as a broad indicator that supplements other available welfare indicators.

PRISMA provides meaningful information useful for poverty monitoring and analysis. In presenting the poverty indicators, the system adopts a "traffic-light" classification system of red, yellow, and green to represent high, average, and low poverty incidences. Thematic maps are generated to show spatial distribution of one or more specific data themes for a particular geographic area. Menus of geographic disaggregation, population, household, and poverty characteristics are available and can be combined with other features. Users can accordingly overlay poverty indicators with other poverty characteristics in bar charts, alter the flexible traffic-light classification of the thematic map, present detailed information about a province or district, export of maps for use in other software applications, and print outputs.

CGE Modeling Frameworks

The CGE economy-wide modeling frameworks consider optimal behavior of economic agents like consumers and producers and are built using a social accounting matrix that considers economic transactions among various sectors and agents in the economy in a consistent manner. These frameworks are suitable for policy simulations with economy-wide repercussions, such as trade liberalization discussed in this book. The model's benchmark reproduces the functioning economy in the base year when there was no policy change. Trade liberalization is then introduced by reducing tariff or nontariff barriers, or both, that will change imports, exports, and domestic prices. Prices in protected sectors fall following the trade barriers' removal and, hence, trade liberalization leads to resource allocation across sectors. Changes in commodity prices, demand, supply, employment, wages, and profit levels corresponding to a new equilibrium lead to changes in national income and its distribution across income groups. These effects are examined by comparing two equilibrium scenarios of *with* and *without* trade liberalization.

Many DMCs have adopted a two-pronged strategy for poverty reduction: economic growth enhancement and direct poverty reduction programs. A CGE modeling framework could be developed for ex ante PIA under both types of programs. It is important to note, however, that there is no single model that fits all programs. Sectors, agents, and linkages in a trade-driven growth strategy would, for example, be different from those in an infrastructure-led growth strategy. Similarly, impact analysis of direct poverty reduction programs on a fair-price scheme for the poor would require a model with different layers of commodity price structures, while an analysis of an employment-generation scheme would detail labor market features.

CGE modeling framework results have provided analytical support for carrying out economic reforms in many developed and developing countries by indicating the quantitative magnitude of welfare increase from reforms. With appropriate household grouping, the major gainers and losers from policy changes could be identified from a model's simulations. Compensation mechanisms could be devised to make all major stakeholders improve their welfare. This process provides insights on how a broad consensus for certain reform packages can be attained (See Parikh et al. 1997 and Panda and Quizon 2000 for similar exercises).

While these frameworks are not commonly used for impact analysis of a specific project, a combination of projects in a particular sector might amount to a kind of policy change with macroeconomic impact. Large-scale poverty reduction programs have an impact on the entire economic system as well as other policy reforms. To capture their impacts, the underlying CGE model must reflect country-specific structural features and generate the right counterfactual, providing the "before-and-after" approach in impact analysis.

Note that PIA carried out through the CGE model might be interpreted as ex-ante impact assessment that could be useful for designing better programs and policies. It allows judging of alternative programs using optimal criteria such as maximizing poverty reduction at a given cost. High-cost projects could thus be avoided. In some cases, trade offs between growth and poverty reduction could be better understood. Similarly, there is a scope for improving a program's effectiveness by reducing leakages. Impact analysis under alternative leakage parameters could help in examining the benefits of controlling the leakages (see Narayana, Parikh, and Srinivasan 1990). Ex-post program monitoring could help in verifying whether the anticipated assumptions on exogenous variables and parameter changes materialized or not. Incorporating the new parameter values consistent with ex-post realization could turn the ex-ante evaluation into an ex-post one.

Anticipated parameter changes corresponding to a simulation run must be clearly spelt out while assessing the policy impact. For example, policy analysis aimed at providing better access for poor groups in employment-generation programs might change the distribution parameter for the poor from such programs. The models might be very sensitive to changes in some key parameters and their values must be chosen after careful scrutiny of the database and the relevant literature.

In CGE models, representative households consist of large groups and might not be homogenous enough for certain programs or policies. Given the differences in income sources and consumption patterns, some households within the group might benefit while others might lose, and average values are not very helpful in such cases. Extending the CGE model to microsimulation is an attempt to extend economic effects analysis, such as prices and wages, to individual household–level data in a survey and is useful to capture intra-group heterogeneity which is an important consideration in PIA. Integration of CGE microsimulation with GIS, such as in the PRISM, adds further value to the spatial dimension of PIA.

Overall, CGE models provide a method of analyzing economy-wide effects of macroeconomic policies. With extensions to new techniques, like microsimulation and poverty mapping, it is possible to examine the poverty impact of macro policies at the micro level. Such approaches would be more satisfactory in the future when micro foundations of macroeconomic analysis are developed. Despite the caveats, CGE-modeling frameworks do help enhance our knowledge of PIA for different types of economic policies.

CGE Modeling Application

Can the Poor in Indonesia Benefit from Trade Liberalization? Agricultural trade barriers remain prevalent among developing countries, raising important questions on whether there is justifiable reason for agricultural protection and what effects might result from farm trade liberalization. Furthermore, as most farm producers are poor farmers, there is also an issue on whether the poor would benefit from trade liberalization.

The CGE model is employed to address these issues by simulating what the likely effects of the Doha Development Agenda would be for a developing country such as Indonesia. The assessment is conducted at the economy-wide level, including welfare and distributional implications for different household groups. Moreover, to view agricultural protection in a broader context, the assessment includes the welfare costs of existing sectoral taxes.

Three scenarios are simulated: a complete removal of tariffs on agricultural products, the first scenario combined with a complete removal of domestic taxes on agricultural products, and full tariff liberalization. The overall results suggest that a removal of agricultural tariffs alone will generate adverse effects, while its combination with the removal of agricultural taxes will create benefits for the economy, households, and the poor. Single sector trade liberalization does not seem a good strategy but more comprehensive trade reform is desirable. In addition, the results of the last simulation provide further evidence of the inefficiency of raising revenue through commodity taxation.

Moreover, the results of near marginal tax incidence indicate that nearly all sectors have already been overtaxed, except for utilities. The existing tax system has distorted the economy so that a unit of revenue collected increases welfare loss. A further elaboration of the welfare costs of the existing commodity taxation reveals that some sectors are relatively much more distorted than others. This applies to both tariffs and domestic indirect taxes, even though the welfare costs of tariffs are relatively less than those of domestic taxes.

Contrasting the first two simulation results further confirms that existing taxation on domestic agricultural commodities is an expensive way of collecting revenue as shown by its associated welfare costs and the potential benefits from its removal. The first simulation results indicate that increasing market access alone will generate more adverse effects for the domestic economy, since all other distortions remain. This policy does not stimulate domestic production, increase employment, or improve welfare. Perhaps, most importantly, the result is not pro-poor. The results of the second scenario, however, are very promising. The removal of both agricultural tariffs and domestic taxes boosts domestic production, which have positive ramifications on the economy. Welfare is improved and the poor benefit.

The detailed results also show that full benefits of trade liberalization cannot be obtained by piecemeal trade liberalization. Liberalizing one sector alone will generate misleading signals for resource allocation. The full tariff liberalization scenario yields the greatest benefits for the poor and for the economy as a whole. This calls for more comprehensive trade liberalization, aligned with domestic industrial and other policies. The government could expand the benefits by further liberalizing both international and domestic markets. This, however, requires strong commitments as well as collaboration with other trading partner countries. The latter is essential since unilateral trade liberalization is not a desirable a course of action, reflecting a key role for the World Trade Organization.

Infrastructure Development and Poverty Alleviation in the PRC. This study assesses the contribution of infrastructure development to poverty reduction in the PRC using a CGE model with disaggregated households, segmented urban and rural labor markets, and endogenous labor supply. The short and long-run implications of improved infrastructure on poverty alleviation are analyzed.

The simulation results show that in the short term, the increase in infrastructure investment promotes outputs of related sectors and creates more employment opportunities for rural migrants, which benefits rural households. From a long-term perspective, the development of infrastructure reduces migration costs and promotes urban employment of rural migrants. But under the background of full employment and restriction of labor mobility, the urban households share more benefits from economic growth and improvement of agriculture labor productivity. However, if the policy loosens the restriction on labor migration from rural to urban areas and makes more rural migrants employed in urban areas, then the welfare of those poor rural households will improve. Reducing transfer costs and promoting employment in urban areas for rural labor are, therefore, the key approaches through which infrastructure makes contributions to poverty reduction.

Higher infrastructure investments promote economic growth and improve all rural households' welfare by creating more off-farm and urban job opportunities. However, as more rural migrants try to work in urban areas, the competition in the urban labor market becomes more intense, bringing adverse effects on the income and well-being of urban households.

The most direct benefit brought by infrastructure improvements to the poor is the reduction of migration costs, which stimulates labor productivity growth in the long run. The lower the migration costs, the more the rural households benefit. Lower migration costs alone, however, have limited effects on economic growth and rural poverty reduction. The improvement of agricultural labor productivity strongly promotes economic growth, but the distribution of the benefits is determined by the scale of labor migration.

CGE-Microsimulation Modeling Application

Economic and Poverty Impacts of Trade Liberalization in Indonesia. The rapid pace of Indonesia's unilateral trade liberalization and the imminent agricultural liberalization arising from the DDA, have been the subject of policy debates. To address this issue, CGE linked to a microsimulation model of the Indonesian economy was developed.

Three policy experiments in line with DDA were undertaken in the study. These are: full elimination of tariffs on agricultural imports, full eliminations of tariffs and indirect taxes on agricultural imports and products, and full elimination of all tariffs on imported products.

The results indicate that removing agricultural tariffs alone generates adverse effects, while the removal of agricultural tariffs coupled with the abolition of agricultural taxes benefits the economy, households, and the poor. An alternative strategy of more comprehensive liberalization involving all sectors, seems the best scenario as the degree of poverty reduction also intensifies. Hence, the general results seem to indicate that the existing tariffs are not only distorting to the economy but are also not pro-poor.

The prevalence of agricultural protection may not be beneficial to the Indonesian economy in the long run, as can be seen from the simulation results of only eliminating agricultural tariff. The presence of cheap agricultural imports as a result of the policy will induce consumers to substitute toward them, resulting in agricultural output contraction and a reduction in the income of farm workers. National poverty headcount, poverty gap, and poverty severity increase. This implies that the already poor, especially agriculture dependent households, become poorer.

In contrast, a more proactive stance of adopting complete farm trade liberalization in which tariffs and indirect taxes on agricultural products were also removed, appears more promising. The policy is consistent with the DDA and seems beneficial to the economy and the poor. Agriculture, industry, and services outputs expand, resulting in an increase in factor returns. In particular, wages of agricultural laborers increase substantially, suggesting that they benefit from the resource reallocation effects. They benefit most especially when compared with other workers. To a large extent, the abolition of domestic agricultural taxes allows domestic agricultural producers to compete with agricultural imports. Disposable incomes of all households increase, while the cost of the commodity basket falls, leading to poverty reduction. As a result, headcount ratio, poverty gap, and poverty severity fall, indicating an improvement in the overall poverty condition.

The last alternative of full tariff elimination appears the best poverty reducing policy. Industrial and services outputs expand, while agricultural output contracts. Industrial exports and imports increase, while agricultural and service imports fall, thereby sustaining the trade surplus. Resources are reallocated away from agriculture toward industry and services. The adjustment impact is a decline in wages and, consequently, income for almost all households. However, this fall is outweighed by the reduction in consumer prices as a result of tariff elimination. Hence, poverty decreases substantially. Nonetheless, the decline in poverty is higher among nonagriculture dependent households, especially those residing in urban areas, where poverty incidence is already the lowest. This benefit may stem from the ability of nonfarm workers to take advantage of additional opportunities as a result of the expansions of the industrial and services sectors. Accordingly, the main challenge for the government is to implement complementary policies especially targeted to farm workers and the poor. Through improved access to the labor market, they would then be able to take advantage of the opportunities being offered by trade liberalization and the DDA.

PRISM—Poverty Reduction Integrated Simulation Model

A CGE-Microsimulation Model linked to a GIS Application. PRISM is an online modeling tool that combines a CGE-microsimulation model and a GIS application for poverty mapping for spatial analysis. All complexities of the modeling aspects are interfaced in a user-friendly way so that users can run simulations and conduct some analyses online with ease.

The modeling tool allows users to conduct scenario analysis by changing some policy parameters in the model, running the simulation, and getting the results online. The economy-wide effects of any changes as a result of the simulation are presented in graphs and tables, which can then be copied to other computer applications. Moreover, the poverty impact for selected regions, provinces, and districts in a country is also presented in dynamic and interactive GIS map to allow spatial analysis to be conducted in an intuitive way. A comparison of poverty impact indicators of two different scenarios has also been made possible with a dual-window, map-viewing facility.

PRISM was developed using the Philippines' CGE-microsimulation model based on the 1994 Social Accounting Matrix and 1994 Family Income and Expenditure Survey. Incorporation of other countries in the system is possible, especially for those countries which already have CGE models developed such as Bangladesh, PRC, Indonesia, Nepal, Pakistan, and Viet Nam.

Trade Liberalization in the Philippines: The Need for Further Reform. The importance of trade liberalization in reducing poverty has received considerable attention from policy makers. Tariff reduction alters relative prices of domestically produced and import goods, leading to the reallocation of resources. The effects on the poor can be traced through several transmission mechanisms such as household income, consumption, unemployment, wages, and relative prices. This study examines the tariff reduction effects on the economy and poverty in the Philippines in 1994–2000 by employing PRISM. Detailed individual household data are integrated in the model to capture the interaction between policy reforms and individual household responses, and their feedback to the general economy. Three scenarios are examined in the paper, namely, low uniform tariff reduction, actual tariff reduction, and full trade liberalization.

Results reveal that, among other effects, tariff reduction reduces domestic prices of imported and locally produced goods. The decline in import prices results in higher imports, while the drop in local prices increases export competitiveness, which in turn promotes higher exports. The nonfood manufacturing sector benefits from both capital reallocation and labor movement. Agricultural wages decline as a result of a drop in agricultural output. The contraction leads to higher unemployment in agriculture. Furthermore, the contraction results in lower capital return in agriculture, lowering rural household income. On the other hand, with the resource reallocation effects favoring industry, particularly nonfood manufacturing, the wages of production workers and capital return in industry increase. Finally, the decline in composite prices as a result of tariff reduction leads to a lower poverty threshold for a given commodity basket leading to favorable effects on all poverty indices. Poverty reductions, however, vary considerably across different household groups.

Limitations of the Studies

The five modeling frameworks discussed in this book are essentially diagnostic tools that can all contribute to the implementation of a comprehensive PIA. Each tool can be used alone or in combination with others at different stages of PIA.

Due to time and resource constraints, however, the tools developed in this book did not cover the whole spectrum of PIA techniques available to policy makers and researchers. The book focuses only on the tools developed by ADB's Economics and Research Department.

Another obvious limitation is that this volume lacks actual examples of projects in which the tools were used. Even though applications of the modeling tools tried to emulate actual policies or policies that could have been adopted by the government or other stakeholders, the selected scenarios may not fully capture the way actual projects, programs, or policies are implemented.

Key Challenges

Conducting a comprehensive PIA for a general project or for a project specifically designed to assist the poor remains a challenge. The difficulties start with getting the key stakeholders to agree to do it. Should they agree, technically complex and difficult issues have to be addressed such as identifying the project's beneficiaries and measuring actual project impact that should be attributed only to the project and free from selection bias.

Many attempts to conduct PIA mostly suffer from insufficient analytical rigor, wrong questions being addressed, and inappropriate timeframes. As a result, there is no single comprehensive PIA that serves as a prototype. This fact is made worse by the requirement that each PIA should be unique, i.e., specifically designed for a particular purpose and for characteristics peculiar to the project being assessed. Therefore, it is not surprising to find that we still know very little about the actual impact of projects on the poor. Moreover, available data are often not useful for conducting a comprehensive PIA and using the data leads to misattributions in terms of timing, topical relevance, and geographical coverage.

On the other hand, people are increasingly aware that good PIA will be very helpful in improving resource allocation. Information from good PIA can be used to help weed out defective pro-poor programs or projects and identify the most effective ones.

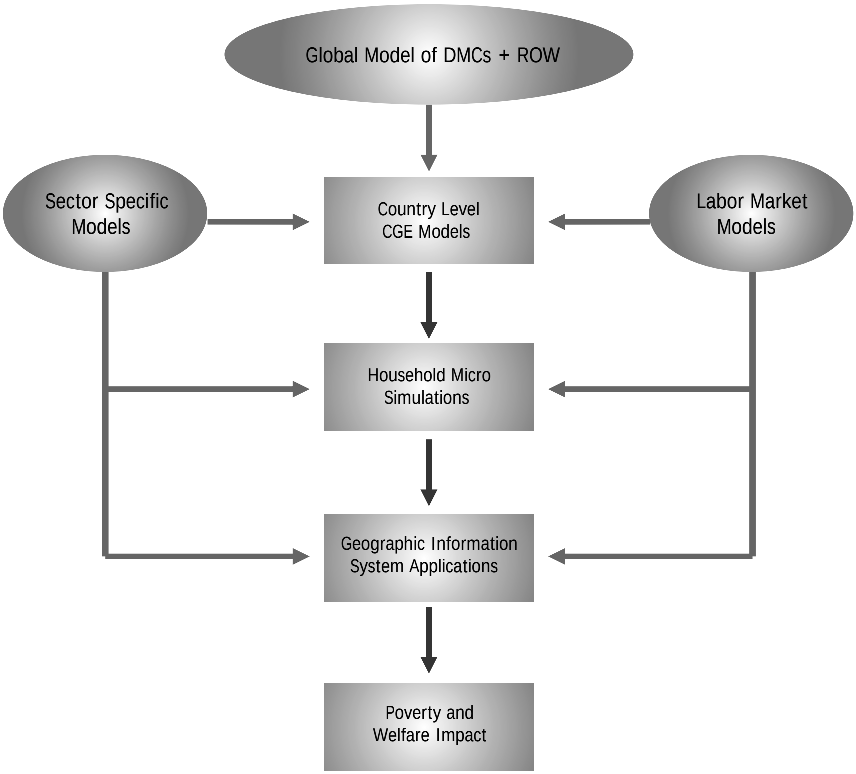
The challenge remains to find ways to conduct a comprehensive PIA which adopts an analytically rigorous approach, answers the right questions, and uses the right timeframe. Specifically, other key challenges include:

- providing more comprehensive and rigorous macro-micro linkages in the modeling tools used;
- focusing on the dynamism of policy interventions and how they affect the overall economy as well as groups targeted by the interventions;
- integrating long-term growth considerations in modeling aspects;
- combining available techniques or approaches in a meaningful and integrative way;
- maximizing all available information from secondary and primary sources starting from general to more specific issues, hence, addressing the issues concerned in a systematic and comprehensive way;
- providing some scenario and sensitivity analyses in the modeling tools developed to provide better and more complete information about all likely impacts; and
- making PIA modeling tools as user-friendly as possible such as by automating some PIA activities to make them easily replicable across topic, sector, or even country.

In terms of modeling aspects, a complete link to the various modeling approaches at global, national, local, and household or individual levels can be provided in a user-friendly way, as partly demonstrated in the PRISM. The schematic representation below illustrates the proposed user-friendly and comprehensive modeling system. At the top level is a global CGE model representing some important DMCs and the rest of the world that link to the individual CGE-microsimulation models and GIS applications. The last two have been integrated in the PRISM.

Moreover, different kinds of modeling tools related to the labor market and for some specific and relevant sectors such as education, health, agriculture, manufacturing, and service sectors can also be incorporated to further enhance the performance of the individual CGE-microsimulation models. In addition, the individual labor market and sectoral models can also be linked to a GIS application to produce separate spatial analysis of the labor market and other sectoral issues. With a complete modeling framework, PIA on wide-ranging issues could be comprehensively conducted and the impact of programs and projects to reduce poverty could thus be traced at global, national, and individual levels.

A Blueprint for PIA Modeling Development and Applications



Source: Authors' blueprint.