



# COMMITMENT TO EQUITY ASSESSMENT: HANDBOOK

*Nora Lustig and Sean Higgins*

COMMITMENT TO EQUITY



## COMMITMENT TO EQUITY ASSESSMENT (CEQ): ESTIMATING THE INCIDENCE OF SOCIAL SPENDING, SUBSIDIES AND TAXES

### HANDBOOK

Nora Lustig and Sean Higgins<sup>†</sup>

September 2013<sup>‡</sup>

### Abstract

This handbook presents a step-by-step guide to applying the incidence analysis used in the multi-country Commitment to Equity project (CEQ). We define the pre- and post-net transfers income concepts, discuss the methodological assumptions used to construct them, explain how taxes, subsidies and transfers should be allocated at the household level, and suggest what to do when the information on taxes and transfers is not included in the household survey. We also describe the indicators that are used to assess the distributive impact, progressivity and effectiveness of social spending, subsidies and taxes. In addition, we present sample Stata code for producing some of the indicators. (For more on CEQ visit [www.commitmenttoequity.org](http://www.commitmenttoequity.org))

Keywords: handbook, taxes and transfers, fiscal incidence, poverty, inequality  
JEL: H22, D31, D63, I32, I38

---

<sup>†</sup> Nora Lustig is Samuel Z. Stone Professor of Latin American Economics ([nlustig@tulane.edu](mailto:nlustig@tulane.edu)) and Sean Higgins is a doctoral student in the Department of Economics, Tulane University ([shiggins@tulane.edu](mailto:shiggins@tulane.edu)).

<sup>‡</sup> Earlier versions of this handbook were published as Tulane University Economics Department Working Paper No. 1119 in April 2011 and No. 1219 in October 2012; and as a CEQ Working Paper No.1 in January 2013. This version was most recently revised in September 2013.

## Table of Contents

### Acknowledgements

#### 1. Introduction

#### 2. Income Concepts and Methodological Assumptions

- i. Income Concepts: Definitions
- ii. When Information on Taxes and Transfers is not in the Survey
- iii. Constructing the Income Concepts: Methodological Assumptions
- iv. Benchmark Case and Sensitivity Analyses
- v. Constructing Market Income
- vi. Constructing Net Market Income
- vii. Constructing Disposable Income
- viii. Constructing Post-fiscal Income
- ix. Constructing Final Income
- x. Complementary Analysis: Tax Expenditure and Subsidized Portion of Social Security

#### 3. Incidence Results and Indicators

- i. Sheet D1 – Reduction in Inequality and Poverty
- ii. Sheet D2 – Effectiveness Indicators
- iii. Sheet D3 – Measures of Progressivity and Horizontal and Vertical Inequality
- iv. Sheet D4 – Incidence by Decile and Socioeconomic Groups
- v. Sheet D5 – Concentration Shares by Decile and Socioeconomic Groups
- vi. Sheet D6 – Income Distribution by Decile and Socioeconomic Groups
- vii. Sheet D7 – Fiscal Incidence Curves and Fiscal Mobility Profiles by Deciles
- viii. Sheet D8 – Concentration Coefficients and Budget Shares for Social Spending and by Program
- ix. Sheet D9 – Coverage and Distribution of Benefits and Beneficiaries by Program
- x. Sheet D10 – Fiscal Mobility Matrices
- xi. Sheet D11 – Engel et al. (1999) Decompositions
- xii. Sheet D12 – Needs vs. Resources
- xiii. Sheet D13 – Cumulative Distribution Functions of Income
- xiv. Sheet D14 – Lorenz Curves and Concentration Curves
- xv. Sheet D15 – Inequality of Opportunity
- xvi. Sheet D16 – Progressiveness of Pensions
- xvi. Sheet D17 – Comparison over Time
- xvii. Sheet D18 – Comparison with Other Studies

### Appendices

#### A. Correcting for Underestimating Number of Beneficiaries

#### B. Definition of Household: Sensitivity Tests

#### C. Predicting Rent to Impute the Value of Owner Occupied Housing

### References

## Acknowledgements

Launched in 2008, the Commitment to Equity (CEQ) framework was designed to analyze the impact of taxation and social spending on inequality and poverty in individual countries and to provide a roadmap for governments, multilateral institutions, and nongovernmental organizations in their efforts to build more equitable societies. Led by Nora Lustig, the CEQ is a project of the Center for Inter-American Policy and the Department of Economics, Tulane University and the Inter-American Dialogue, with Peter Hakim as co-director. In 2013, the CEQ partnered with the World Bank to launch the project *CEQ and World Bank: The Distributional Impact of Fiscal Policy* in Armenia, Ethiopia, Indonesia, Jordan, South Africa and Sri Lanka

This handbook was written with invaluable inputs and suggestions from a large number of people. Jim Alm, Carola Pessino, and John Scott provided essential contributions and guidance from the project's inception. We are also greatly indebted to the members of the CEQ-Latin America Advisory Board. In particular, we wish to thank Jere Behrman, Nancy Birdsall, Otaviano Canuto, Mauricio Cárdenas, Fernando Carrera Castro, Luis Castilla, Louise Cord, Rolando Cordera, Augusto de la Torre, Ludovico Feoli, Francisco Ferreira, Ariel Fiszbein, Juan Alberto Fuentes Knight, Juan Carlos Gómez Sabaíni, Carol Graham, Rebeca Grynspan, Martin Hopenhayn, Santiago Levy, Luis F. Lopez-Calva, Mario Marcel, Jonathan Menkos, Carmelo Mesa-Lago, Judith Morrison, Hugo Noé Pino, José Antonio Ocampo, Daniel Ortega, Tamara Ortega Goodspeed, Guillermo Perry, Jeffrey Puryear, David Roodman, Ana María Sanjuan, Michael Shifter, Vito Tanzi, and Andras Uthoff.

Important recent revisions have been largely guided by the feedback received from the World Bank team and the Advisory Committee of the CEQ and World Bank project *The Distributional Impact of Fiscal Policy*. In particular, we are very grateful to Jaime Saavedra as well as to Gabriela Inchauste and her collaborator Catherine Lee, and peer reviewers Shubham Chaudhuri, Andrew Dabalen, Luis F. Lopez-Calva and Luis Servén from the World Bank; and, advisors Francois Bourguignon, Gary Burtless, David Coady, Robert Gillingham, Jorge Martínez-Vasquez, Cormac O'Dea, David Phillips, Ian Preston, Sally Wallace, and Stephen Younger. We are also highly indebted to Jean-Yves Duclos.

The Handbook has also benefited enormously from the country teams' important contributions to the methodological discussions and revisions. For that, we are grateful to Shamma Alam, Rythia Afkar, Florencia Amábile, Nisha Arunatilake, Marisa Bucheli, Margarita Beneke de Sanfeliu, Maynor Cabrera, Eliana Carranza, Andres Castañeda, Dante Contreras, Camilo Gomez Osorio, George Gray Molina, Carlos Hurtado, Verónica Paz Arauco, Miguel Jaramillo, Jon Jellema, Wilson Jiménez, Cristina Llerena, Mashekwa Maboshe, Yusuf Mansur, Marcela Melendez, Hilda Estuardo Morán, José Andrés Oliva, Claudiney Pereira, Julio Ramirez, Máximo Rossi, Jaime Ruiz-Tagle, Pablo Sauma, Nistha Sinha, Barbara Sparrow, William Swanson, Juan Diego Trejos, Eyasu Tsehaye, Paolo Verme, Matthew Grant Wai-Poi, Tassew Woldehanna, Ingrid Woolard, Ernesto Yáñez, and Precious Zikhali.

At numerous conferences and workshops, people contributed to discussions on the methodological issues explored here, and others provided comments on earlier versions of the handbook; we would like to thank in particular Maria Socorro Bautista, Andrew Berg, Benedict Clements, Christian Daude, Manuel Deshon, Joost Draaisma, Norbert Fiess, Robert Gillingham, Samantha Greenspun, Margaret Grosh, Friederike Koehler, Daniel Lederman, Kathy Lindert, Maria Ana Lugo, Christina Malmberg-Calvo, Angel Melguizo, Emiro Molina, Jose Molinas, Judith Morrison, Ahmed Moumami, Eduardo Ortiz-Juarez, Jacob Ricker-Gilbert, Jamele Rigolini, Tomas Rosada, Eliana Rubiano, Whitney Ruble,



Pablo Sanguinetti, Abebe Shimeles, Tim Smeeding, Dan Teles, Teresa Ter-Minassian, Erwin Tiongson, Dominique van de Walle, Renato Vargas, Adam Wagstaff, Quentin Wodon, and participants of the Commitment to Equity Workshops (hosted by Tulane University and CIPR, New Orleans, October 2010; Universidad Torcuato di Tella, Buenos Aires, December 2010; and the Inter-American Dialogue, Washington, D.C., November, 2011), the Workshop on Fiscal Incidence in LAC (World Bank, Washington, D.C., May 2012), Fiscal Policy for an Equitable Society (World Bank, Washington, D.C., June 2013), Fiscal Incidence Analysis for Selected African Countries (African Development Bank, Tunis, August 12, 2013).

We are indebted to Shaohua Chen for answering our incessant questions about the methodologies used by the World Bank's PovcalNet, to Guillermo Cruces, Leonardo Gasparini, Leonardo Lucchetti, and Leonardo Tornarolli for answering similar questions about CEDLAS and the World Bank's Socio-Economic Database for Latin America and the Caribbean (SEDLAC), to David Phillips for answering these questions about the Institute for Fiscal Studies' research, to Abdelkrim Araar and Jean-Yves Duclos for answering our questions about their Distributional Analysis Stata Package (DASP) and providing us with additional ado files, to Rafael Osorio, Sergei Soares, and Pedro Souza at the Instituto de Pesquisa Econômica Aplicada for providing us with the Stata code to implement their methodology to correct for underestimation of the number of cash transfer beneficiaries, and to the Fiscal Affairs department at the International Monetary Fund for providing us with the Stata code to estimate the indirect effects of price increases using input-output tables.

Specific sections of this handbook relied substantially on inputs and feedback from others. We are very grateful to Gary Burtless, David Phillips, and Paolo Verme for authoring boxes. The section on Inequality of Opportunity is based on a write-up sent to the authors by Norbert Fiess. The section on Fiscal Mobility Matrices is based on a paper written by the authors (Higgins and Lustig, 2013) which benefitted greatly from conversations with and comments from François Bourguignon, Satya Chakravarty, Nachiketa Chattopadhyay, Jean-Yves Duclos, Francisco Ferreira, Gary Fields, James Foster, Peter Lambert, Darryl McLeod, John Roemer, Jon Rothbaum, Shlomo Yitzhaki, and participants of the Symposium on Ultra-Poverty hosted by the Institute for International Economic Policy at George Washington University, Washington, D.C., March 2012; "Well-being and inequality in the long run: measurement, history and ideas" hosted by Universidad Carlos III de Madrid and the World Bank, Madrid, May-June 2012; the annual meeting of the Latin American and Caribbean Economic Association (LACEA), Lima, November 2012; the XX Meetings of the Research Network on Inequality and Poverty (NIP), Washington, D.C., May 2013; and the annual meetings of the Society for the Study of Economic Inequality (ECINEQ), Bari, Italy, July 2013.

Last but not least, the preparation of this handbook would not have been possible without the research assistance provided by Mariellen Jewers and Emily Travis.

Since its inception, the CEQ has received financial support from Tulane University's Center for Inter-American Policy and Research, the School of Liberal Arts and the Stone Center for Latin American Studies as well as the Canadian International Development Agency (CIDA), the Development Bank of Latin America (CAF), the General Electric Foundation, the Inter-American Development Bank (IADB), the International Fund for Agricultural Development (IFAD), the Norwegian Ministry of Foreign Affairs, the United Nations Development Programme's Regional Bureau for Latin America and the Caribbean (UNDP/RBLAC), and the World Bank.

Of course, the authors remain fully responsible for any remaining errors or omissions.

## 1. Introduction

The Commitment to Equity Assessment (CEQ) uses standard incidence analysis<sup>1</sup> to address the following three questions: How much redistribution and poverty reduction is being accomplished in each country through social spending, subsidies and taxes? How progressive are revenue collection and government spending? Within the limits of fiscal prudence, what could be done to increase redistribution and poverty reduction in each country through changes in taxation and spending? CEQ is among the first efforts to comprehensively assess the tax/benefit system in developing countries (including indirect subsidies and taxes and in-kind benefits in the form of free education and health care) and to make the assessment comparable across countries and over time. Applications of CEQ to particular countries and comparative analyses of these results can be found on the CEQ website, <http://commitmenttoequity.org>, and, for six Latin American countries, in a special issue of the *Public Finance Review*.<sup>2</sup>

The purpose of this handbook is to present a step-by-step guide to applying the incidence analysis used in CEQ. The handbook has been written to guide researchers in the completion of the Master Workbook Template, a spreadsheet file that contains all the information used and produced by CEQ. However, the handbook can also be used as a stand-alone document for those interested in methodological and practical approaches to carry out fiscal incidence analysis.

The basic incidence analysis described in this handbook is point-in-time rather than lifecycle and does not incorporate behavioral or general equilibrium modeling. That is, we do not claim that the “pre-fisc” income obtained from this exercise equals the true counter-factual pre-fisc income in the absence of taxes and transfers. It is a first-order approximation. Despite being a standard incidence analysis that does not incorporate indirect effects, the analysis is not a mechanically applied accounting exercise. We analyze the incidence of taxes by their (assumed) economic rather than statutory incidence. For instance, we assume that individual income taxes and contributions (both by employee and employer) are borne by labor in the formal sector and consumption taxes (on both final goods and inputs, using input-output tables for the latter) are fully shifted forward to consumers. In the case of consumption taxes we take into account the lower incidence associated with own-consumption and informality.

---

<sup>1</sup> For a description, applications and limitations of standard incidence analysis see, for example, Adema and Ladaique (2005), Alleyne et al. (2004), Atkinson (1983), Bergh (2005), Bourguignon and Pereira da Silva (2003), Barr (2004), Barros et al. (2009), Birdsall et al. (2008), Breceda et al. (2008), Dilnot et al. (1990), Ferreira and Robalino (2010), Fiszbein et al. (2009), Grosh et al. (2008), Goñi et al. (2011), Kakwani (1977), Lambert (2002), Lora (2006), Morra et al. (2009), Lustig (2000), O'Donnell et al. (2008), Shah (2003), Suits (1977), van de Walle and Nead (1995), World Bank (2000/2001, 2006, 2009b, 2011).

<sup>2</sup> Specifically, see Lustig, Pessino, and Scott (2013) for an overview, Lustig and Pessino (2013) for Argentina, Paz Arauco et al. (2013) for Bolivia, Higgins and Pereira (2013) for Brazil, Scott (2013) for Mexico, Jaramillo (2013) for Peru, and Bucheli et al. (2013) for Uruguay.

We attempt to cover a very broad spectrum of taxes and transfers. Taxes include direct and indirect taxes, and for both subsidies and indirect taxes, we propose to analyze both those on final consumption goods and those on inputs. Spending covers transfers and indirect subsidies, especially on energy and agricultural inputs. Throughout the handbook, we refer to transfers and social spending interchangeably; i.e., “transfers” is intended to include in-kind benefits from public spending on education and health. At this point, our framework does not include financial subsidies: e.g., access to government loans that charge below market interest rates.

The handbook is organized as follows. Section 2 explains how to construct the income concepts used in the incidence analysis. It also explains how to construct the “income” concepts for surveys that include only consumption. Constructing the income concepts is the fundamental building block of incidence analysis. It entails the process by which taxes, subsidies and transfers are allocated to each household to assess how incomes—and, thus, inequality and poverty indicators—change with fiscal policy. Section 3 describes the indicators that are used to assess the distributive impact, who bears the burden and who benefits, and the progressivity and effectiveness of social spending, subsidies and taxes. In addition, Section 3 explains how to complete the accompanying Master Workbook Template. Sample Stata code for undertaking the analysis is included throughout.

The Master Workbook Template (available to researchers participating in CEQ projects) is divided into four main sections, each with a number of sheets. The first section, Country Background Information (also referred to as Section A) is designed to provide background information on the country, including the historical evolution of poverty and inequality, macroeconomic information, and information about the tax system, pension system, subsidies, and public education and health sectors. The next section, Survey Information (or Section B) is meant to provide general information about the household survey being used, as well as the exact questions used for every component of income. The third section, Methodological Aspects (Section C) provides transparency on the *allocation method* used for each indirect tax, direct transfer, in-kind transfer, and subsidy. The fourth section, Incidence Results and Indicators (Section D) presents the results from the incidence analysis. It provides an array of poverty, equity, efficiency, and effectiveness indicators to address the questions posed in CEQ. It is data intensive, requires inputs from researchers from their Stata output, and uses formulas to automatically calculate many indicators from inputs. Instructions to complete each sheet of Sections A, B, and C are included on the respective sheets of the Master Workbook Template; more detailed instructions for Section D are given in Section 3 of this handbook. Our hope is that researchers will be able to make use of the many definitions and indicators described in this handbook regardless of whether they are using it in conjunction with the Master Workbook Template.<sup>3</sup>

---

<sup>3</sup> The Commitment to Equity Master Workbook and other tools are protected by the copyright laws of the United States and international treaties and conventions and may only be used with permission. Unauthorized reproduction and distribution are strictly prohibited. All rights reserved. For permissions, contact Professor Nora Lustig, [nlustig@tulane.edu](mailto:nlustig@tulane.edu).

## 2. Income Concepts and Methodological Assumptions

### i. Income Concepts: Definitions

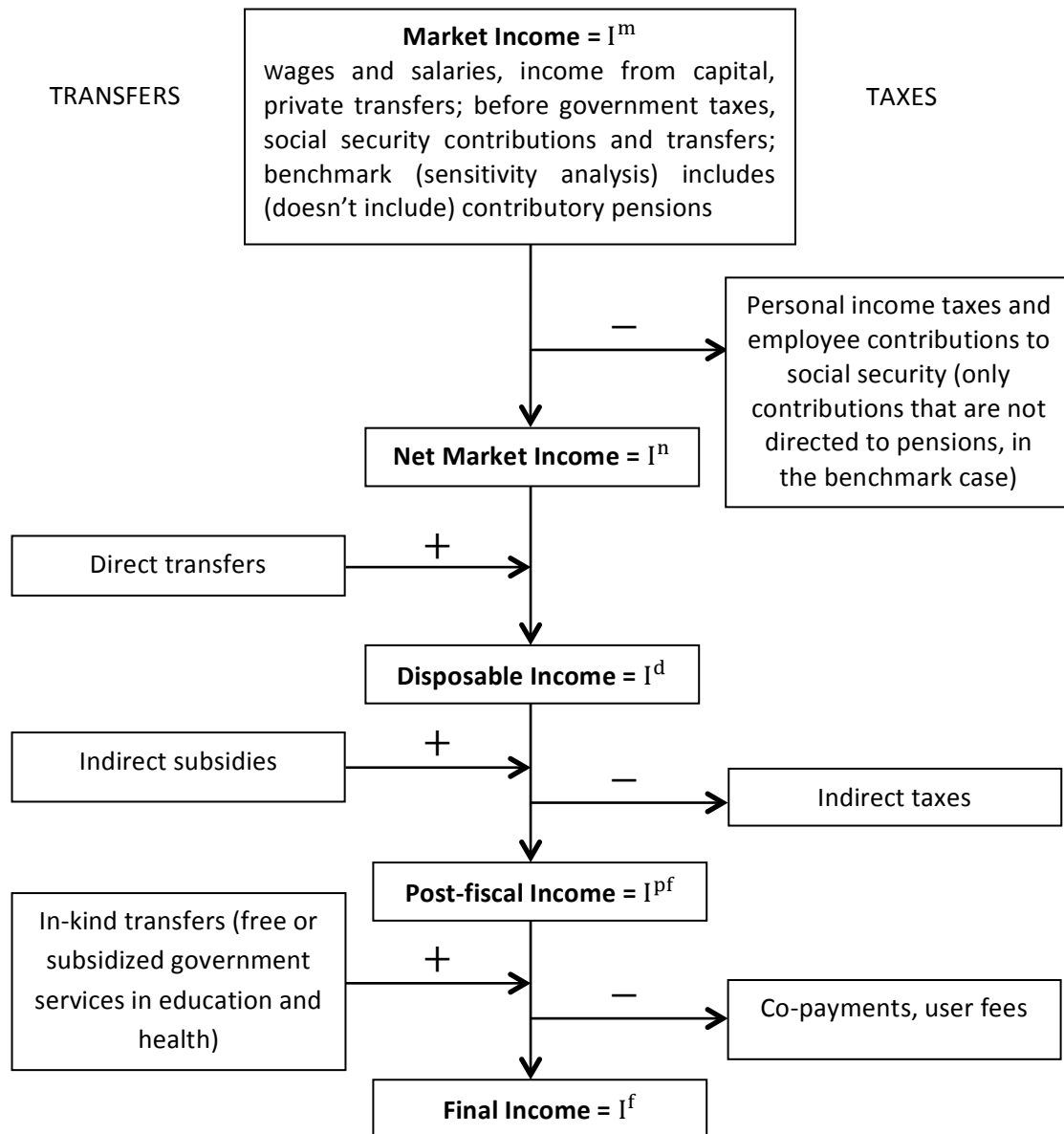
As usual, any incidence study must start by defining the basic income concepts. In our study we use five: market, net market, disposable, post-fiscal and final income. The categories included in each concept are shown in Diagram 1 and described in more detail below. One area in which there is no agreement is how pensions from a pay-as-you-go contributory system should be treated. Arguments exist in favor of both treating contributory pensions as part of market income because they are deferred income (Breceda et al., 2008; Immervoll et al., 2009) or as a government transfer especially in systems with a large subsidized component (Goñi et al., 2011; Immervoll et al., 2009; Lindert et al., 2006; Silveira et al., 2011). Since this is an unresolved issue, in our study we defined a benchmark case in which contributory pensions are part of market income. We also include a sensitivity analysis in which pensions are classified under government transfers, which we call Sensitivity Analysis 1.<sup>4</sup>

To ensure comparability across countries and ensure that we always test the sensitivity of our results to the choice of how to treat pensions, we recommend constructing all of the income concepts for the Benchmark Case and Sensitivity Analysis 1 and producing the results for both of these scenarios. The Master Workbook Template already has space incorporated to describe the construction of income concepts in both scenarios and to present results in both scenarios. In addition, we recommend implementing additional sensitivity analyses to test robustness of results. For example, the researcher might test the sensitivity of their results to different assumptions about economies of scale or adult equivalence; to different allocation methods for various tax and transfer programs; to different assumptions about tax avoidance and evasion; to using regression methods vs. direct identification for the value of owner occupied housing; and so on.

---

<sup>4</sup> Immervoll et al. (2009) do the analysis under these two scenarios as well.

**Diagram 1 – Definitions of Income Concepts: A Stylized Presentation**



Note: in some cases we also present results for “final income\*” which is defined as disposable income plus in-kind transfers minus co-payments and user fees.

More detailed definitions of the income concepts are as follows.

*Market income* is defined as:

$$I^m = W + IC + SC + IROH + PT' + SSP \text{ (benchmark)}$$

$$I^{ms} = W + IC + SC + IROH + PT \text{ (sensitivity analysis)}$$

Where,

$I^m, I^{ms}$  = market income<sup>5</sup> in benchmark and sensitivity analysis, respectively.

$W$  = gross (pre-tax) wages and salaries in formal and informal sector; also known as earned income. Note that if payroll taxes or other taxes whose statutory incidence is not on the employee (but whose economic incidence is assumed to fall on the employee in the form of lower wages) are included in the analysis, wages must be “grossed up” to the unobserved pre-payroll tax counterfactual by adding in payroll taxes (which will later be subtracted as a direct tax) as part of  $W$ .

$IC$  = income from capital (dividends, interest, profits, rents, etc.) in formal and informal sector; excludes capital gains and gifts.

$SC$  = self-consumption, also known as production for own consumption or self-production;

$IROH$  = imputed rent for owner occupied housing; also known as income from owner occupied housing.

$PT$  = private transfers (remittances and other private transfers such as alimony).

$SSP$  = retirement pensions from contributory social security system.

*Net Market income* is defined as:

$$I^n = I^m - DT - SSC \text{ (benchmark)}$$

$$I^{ns} = I^{ms} - DT - SSC^s \text{ (sensitivity analysis)}$$

Where,

$I^n, I^{ns}$  = net market income in benchmark and sensitivity analysis, respectively.

$DT$  = direct taxes on all income sources (included in market income) that are subject to taxation.

$SSC, SSC^s$  = respectively, all contributions to social security except portion going towards pensions<sup>6</sup> and all contributions to social security without exceptions.

*Disposable income* is defined as:

$$I^d = I^n + GT \text{ (benchmark)}$$

$$I^{ds} = I^{ns} + GT + SSP \text{ (sensitivity analysis)}$$

Where,

$I^d, I^{ds}$  = disposable income in benchmark and sensitivity analysis, respectively.

$GT$  = direct government transfers; mainly cash but can include transfers in kind such as food.

$SSP$  = retirement pensions from contributory social security system.

---

<sup>5</sup> Market income is sometimes called primary income.

<sup>6</sup> Since here we are treating contributory pensions as part of market income, the portion of the contributions to social security going towards pensions are treated as ‘saving.’



*Post-fiscal income* is defined as:

$$I^f = I^d + \text{IndS} - \text{IndT} \text{ (benchmark)}$$

$$I^{fs} = I^{ds} + \text{IndS} - \text{IndT} \text{ (sensitivity analysis)}$$

Where,

$I^f, I^{fs}$  = post-fiscal income in benchmark and sensitivity analysis, respectively.

IndS = indirect subsidies (e.g., lower electricity rates for small-scale consumers).

IndT = indirect taxes (e.g., value added tax or VAT, sales tax, etc.).

*Final income* is defined as:

$$I^f = I^f + \text{InkindT} - \text{CoPaym} \text{ (benchmark)}$$

$$I^{fs} = I^{fs} + \text{InkindT} - \text{CoPaym} \text{ (sensitivity)}$$

Where,

$I^f, I^{fs}$  = final income in benchmark and sensitivity analysis, respectively.

InkindT = government transfers in the form of free or subsidized services in education and health; urban and housing.

CoPaym = co-payments, user fees, etc., for government services in education and health.<sup>7</sup>

Because some countries do not have data on indirect subsidies and taxes, we also defined *Final income\** =  $I^{f*} = I^d + \text{InkindT} - \text{CoPaym}$ .

## **ii. When Information on Taxes and Transfers is not in the Survey**

Unfortunately the information on direct and indirect taxes, transfers in cash and in-kind, and subsidies cannot always be obtained directly from household surveys. Thus, one of the most important aspects of CEQ is a detailed description of how each component of income is calculated (for example, directly drawn from the survey or simulated) and the methodological assumptions that are made while calculating them. In many cases, the authors must choose a method based on the institutional structure of the country and the data available. CEQ relies on local experts as a crucial part of the research team for precisely this reason. In many cases, the researcher must exercise judgment based on their knowledge of the country's institutions, spending, and revenue collection, and on the availability and quality of the data. It is of the utmost importance to always describe what method was used for a particular tax or transfer, the reasoning for using this method, and—whenever possible—the sensitivity of the results to using alternative methods.

When taxes and transfers can be obtained directly from the household survey, we call this the *Direct Identification Method*. When the direct method is not feasible, one can use the inference, simulation,

---

<sup>7</sup> One may also include participation costs, such as transportation costs or foregone incomes because of use of time in obtaining benefits. In our study, they were not included.

imputation or alternate survey methods (described in more detail below). As a last resort, one can use secondary sources: e.g., incidence or concentration shares by quintiles or deciles that have been calculated by other authors as is done by Goñi et al. (2011) for instance. Finally, if none of these options can be used for a specific category, the analysis for that category will have to be left blank. The six methods one can use to allocate taxes and transfers are described below.

#### *Direct Identification Method*

On some surveys, questions specifically ask if households received cash benefits from (paid taxes to) certain social programs (tax and social security systems), and how much they received (paid). When this is the case, it is easy to identify transfer recipients and taxpayers, and add or remove the value of the transfers and taxes from their income, depending on the definition of income being used.

#### *Imputation Method*

The imputation method uses some information from the survey, such as the respondent reporting attending public school or receiving a direct transfer in a survey that does not ask for the amount received, and some information from either public accounts, such as per capita public expenditure on education by level, or from the program rules.

#### *Inference Method*

Unfortunately, not all surveys have the information necessary to use the direct identification method. In some cases, transfers from social programs are grouped with other income sources (in a category for “other income,” for example). In this case, it might be possible to infer which families received a transfer based on whether the value they report in that income category matches a possible value of the transfer in question.

#### *Simulation Method*

In the case that neither the direct identification nor the inference method can be used, transfer benefits can sometimes be simulated, determining beneficiaries (taxpayers) and benefits received (taxes paid) based on the program (tax) rules. For example, in the case of a conditional cash transfer that uses a proxy means test to identify eligible beneficiaries, one can replicate the proxy means test using survey data, identify eligible families, and simulate the program’s impact. However, this method gives an upper bound, as it assumes perfect targeting and no errors of inclusion or exclusion. In the case of taxes, estimates usually make assumptions about informality and evasion.<sup>8</sup>

The four methods described above rely on at least some information taken directly from the household survey being used for the analysis. As a result, some households receive benefits, while others do not, which is an accurate reflection of reality. However, in some cases the household survey analyzed lacks the necessary questions to assign benefits to households. In this case, there are two additional methods.

#### *Alternate Survey*

When the survey lacks the necessary questions, such as a question on the use of health services or health insurance coverage (necessary to impute the value of in-kind health benefits to households), an alternate survey may be used by the author to determine the distribution of benefits. In the

---

<sup>8</sup> For more on tax avoidance and evasion in developing countries, see Alm, Bahl, and Murray (1991).

alternate survey, any of the four methods above could be used to identify beneficiaries and assign benefits. Then, the distribution of benefits according to the alternate survey is used to impute benefits to all households in the primary survey analyzed; the size of each household's benefits depends on the quantile to which the household belongs. Note that this method is more accurate than the secondary sources method below, because although the alternate survey is somewhat of a "secondary source," the precise definitions of income and benefits used in CEQ can be applied to the alternate survey.

#### *Secondary Sources Method*

When none of the above methods are possible, secondary sources that provide the distribution of benefits (taxes) by quantile may be used. These benefits (taxes) are then imputed to all households in the survey being analyzed; the size of each household's benefits (taxes) depends on the quantile to which the household belongs.

NOTE: It is very important to specify which identification method is used for each transfer program, tax, etc. This information should be explicitly mentioned in the accompanying Master Workbook Template.

### **iii. Using Consumption Instead of Income**

In the literature on incidence analysis, both income and consumption have been used as the basic welfare indicator. Typically, the incidence of direct taxes and transfers is calculated using income and for the incidence of indirect taxes and subsidies some authors recommend using consumption (e.g., Abramovsky, Attanasio, and Phillips, 2011). However, for a comprehensive analysis, one or the other must be chosen as the indicator of wellbeing.<sup>9</sup> Some thoughts on the choice between income and consumption are given in Box 1.

#### **Box 1. On using consumption or income**

*Gary Burtless, Senior Fellow and John C. and Nancy D. Whitehead Chair,  
Brookings Institution*

Ideally, lifetime consumption (or consumption per year) would be the best measure for an incidence analysis, mainly because it represents our best gauge of long-term well-being. However, this measure is not practical given the data limitations we face in every country, rich and poor. If we use an annual measure of income or consumption our choice should be guided by the best (meaning "most accurate available") basic source of data available to us. This will vary by country and probably by income class within a

---

<sup>9</sup> Coudouel, Hentschel, and Wodon (2002) argue that consumption is a better measure for a number of reasons. Although both are underreported (Brewer and O'Dea, 2012), there is substantial evidence that consumption is better measured for the poor (Meyer and Sullivan, 2003). Consumption is smoothed to a greater degree than income (although income is also smoothed, even among the agricultural workers who are often used as an example of people facing volatile incomes; see Murdoch (1995)). A main advantage of income, also noted by Coudouel, Hentschel, and Wodon (2002), is that it can be disaggregated by source, which can be especially appealing for a fiscal incidence analysis.

country. The most accurate information is likely to be that which is easiest for household heads to report. In rich countries, a lot of evidence suggests it is easier to report income sources (since most households have few of them) than it is to report consumption (which has many categories and time frames, and consequently is very hard for people to report accurately). In poor countries it is easy to believe that a large proportion of people will find it easier to report consumption than income, since income may fluctuate much more than it does in rich countries and be derived from many sources (including irregular transfers from or to family members outside the household). Of course, in many countries the available distributional information will be constrained by the actual surveys that have been administered. If only consumption surveys are available, that's what the analysis must use; if only income surveys are available, analysts will have to focus on income.

When consumption is chosen, for example because income data is unavailable or unreliable, we equate consumption to disposable “income”, then work backwards (i.e. subtract out transfers) to get to net market “income” since  $\text{net market income} + \text{transfers} = \text{disposable income} \Rightarrow \text{disposable income} - \text{transfers} = \text{net market “income.”}$ <sup>10</sup>

Note that consumption data is equal to expenditures on non-durables *plus* consumption of own production *plus* the flow value from use of durables owned by the household. Here we leave out the latter except for the case of housing: i.e., we include the imputed rent for owner's occupied housing (explained in greater detail below) but do not calculate the imputed value from use of other durables owned by the household. Although the latter should be included from a theoretical standpoint, it requires information about the value and age of assets owned, or at a minimum on assets owned and average prices for these assets. If you have reliable data to estimate the value from use of assets other than housing, you can perform an additional sensitivity analysis including these components in income. If you use consumption do not include the value of consumer durable purchases (whether in cash or credit) because these are extraordinary expenditures.

After equating consumption to disposable income, one must “work backwards” to construct net market income and market income. To construct net market income, one would use the equation

---

<sup>10</sup> Some people have thought that consumption should be equated to post-fiscal rather than disposable income. The reason we equate consumption to disposable (rather than post-fiscal) income is as follows. First note that  $\text{post-fiscal income} = \text{disposable income} - \text{indirect taxes} + \text{indirect subsidies}$ , or equivalently  $\text{disposable income} = \text{post-fiscal income} + \text{indirect taxes} - \text{indirect subsidies}$ . Since consumption reported in the surveys is based on prices that include indirect taxes (and are net of indirect subsidies), we should be equating it to disposable income which also includes indirect taxes and is net of indirect subsidies based on the second equation above. To illustrate the point about indirect subsidies, suppose a person pays \$10 for their electricity bill, which actually has a market value of \$15, where the government is subsidizing the extra \$5. In the survey the person will report what they spent, which is \$10. So we need to equate reported consumption with disposable income, and then we will add in the \$5 indirect subsidy when we move from disposable to post-fiscal income.

disposable income – transfers = net market income. Note that in rare cases, this might result in a negative net market income, in which case we truncate net market income at 0.<sup>11</sup>

Then to continue working backwards to market income, we use the equation market income = net market income + direct taxes.

To determine direct taxes paid, information on labor income and property ownership would be necessary. If the survey has consumption data only and does not contain information on labor income, one possibility is to attempt to estimate the proportion of net market “income” (i.e., consumption minus transfers) that comes from wages vs. self-employment income. To do this, regress consumption per capita on the number of wage earners, average education of wage earners, average age of wage earners, number of self-employed, average education of self-employed, and average age of self-employed. These coefficients can be applied to the corresponding variables in each household to predict the proportion of consumption from wages (this would equal the coefficients for the first three explanatory variables times the values of these variables for the household, divided by their total predicted consumption) and the proportion of consumption from self-employment (this would equal the coefficients for the latter three explanatory variables times their values times the values of these variables for the household). Once the proportion of consumption attributable to wages and self-employment income has been determined, individual income taxes can be estimated to “work backwards” to market income, using the rules of the tax rates on wages and self-employment income.

If data on labor income is not available and the above method is not possible, two remaining options should be attempted: an *alternate survey* that does have data on labor incomes and other characteristics could be used and mapped back to the primary data set, or *secondary source* estimates of direct taxes paid by consumption decile can be used. If these are also not available, the last resort is to not compute direct taxes and use net market “income” as the baseline for the analysis.

When only consumption data is available, an alternative to equating consumption to disposable income is to attempt to account for savings. Because savings data in developing countries are notoriously bad, we do not attempt to account for savings in the benchmark case. However, the authors may wish to perform an additional sensitivity analysis in which they do account for savings. If data is available on savings rate by consumption decile (or other population group), one can add the appropriate percentage of imputed savings to households at each consumption decile. Note that when this is done, households’ consumption rank should be measured in the same way—to the extent possible—as it was by the secondary source from which the savings rates by decile were obtained. In other words, if the secondary source did not include imputed rent for owner occupied housing in their consumption variable, the researcher should create a new consumption variable to

---

<sup>11</sup> These cases are indeed rare in the benchmark case: for example, in a study for Armenia, this only occurred with four observations in the benchmark case. However, in Sensitivity Analysis 1 it is more common because contributory pensions need to be subtracted when moving backwards from disposable to net market income since they are assumed to be a government transfer, and pensions can be quite sizeable.

match the secondary source's and determine households' consumption deciles by this new variable, solely for the purpose of allocating indirect taxes (for other calculations, the researcher would use the income or consumption variable they had constructed following the instructions in this handbook).

#### iv. Constructing the Income Concepts: Methodological Assumptions

To construct the income concepts using the above definitions, one must have access to micro-data from a recent household survey with information on income and, ideally, consumption. The information from this data set will be combined with data on taxes and transfer programs from public sector accounts. When constructing the income definitions, we make the following methodological assumptions.

##### *Definition of Household*

We adopt the definition of a household used by LIS, SEDLAC, and (in most cases) the World Bank's PovcalNet, which excludes external members of the household: boarders (*inquilinos* in Spanish and *pensionistas* in Portuguese), live-in domestic servants, and (if applicable) their families are not considered part of the household, and should not be included in any income calculations. That is, if each observation in your data set is a household (known as *wide format*), they should not be included in the number of members of the household, and their income will not be included in the household aggregate income or consumption.<sup>12</sup> If each observation in your data set is an individual (known as *long format*), the boarders, live-in domestic servants, and their families should be dropped from the data set.<sup>13</sup> In practice, rather than dropping individuals from the data set, it can be beneficial to create a dummy variable that marks individuals that should be used in calculations, then include an if-condition in the calculations. This allows one to use the "dropped" individuals in other calculations if necessary—for example, to perform a sensitivity analysis of the decision to not include them in the calculations—without having to go back to the original version of the data set before they were dropped. For example, in an individual-level data set, if there is a variable called *status* which equals 1 for the household head, 2 for spouse of the household head, 3 for child of

---

<sup>12</sup> Consider the following example: in an income survey, if the household head earns \$100 and then pays the servant \$10, the survey data will show us exactly these numbers: \$100 and \$10. We drop the servant (and their income) before making household aggregates because otherwise we would aggregate  $\$100 + \$10 = \$110$  but that would be double counting that \$10. In the case of a consumption survey (and ignoring savings), the household (excluding servant) will consume its \$100, \$10 of which shows up as expenditure on the servant's income. Then the servant also consumes their \$10 of income. If we aggregate without dropping the servant we would have  $\$100 + \$10 = \$110$ , again double counting the \$10 that was "consumed" when the household paid the servant, then consumed again by the servant.

<sup>13</sup> Note that some studies do not drop boarders and domestic servants from the calculations, but instead count them as a *separate household*. The implications of adopting one method rather than the other have yet to be rigorously explored, but "exploratory analysis for some countries suggests that for the most part results are not significantly affected by this decision" (CEDLAS and the World Bank, 2012, p. 15); a table summarizing this exploratory analysis can be found in the appendix.



household head, 4 for other relative of household head, 5 for non-relative in the same household (excluding boarders, domestic servants, and their families), 6 for boarder, 7 for live-in domestic employee, and 8 for relative of domestic employee, a dummy variable could be created in Stata with<sup>14</sup>

```
generate i=(status<=5) // this is equivalent to the more long-winded
                        // generate i=0
                        // replace i=1 if status<=5
```

Then, in all of the subsequent calculations, the condition `if i==1` would need to be included to “drop” the boarders, domestic servants, and their families.

When dropping households (or marking them with `i==0`) it is necessary to re-adjust expansion factors so that the sum of the expansion factors of the non-dropped (or `i==1`) individuals still sums to the total population in the country.

Note that—as usual—poverty and inequality calculations will be in terms of individuals rather than households. In other words, the poverty headcount ratio will equal the proportion of individuals below the poverty line, not the proportion of households below the poverty line. If poor households tend to be larger than non-poor households, the former will be higher than the latter.

#### *Adult Equivalence and Economies of Scale*

CEQ uses household per capita income or consumption, and thus does not adjust for adult equivalence or economies of scale within households. For each income concept, total household income for the respective concept is divided by the total number of members in the household. As explained above, total household income should not include the income of boarders, domestic servants, and their families, and the total number of members in the household should not include them either. The author may want to include additional sensitivity analyses where they test the sensitivity of the results to different assumptions about economies of scale or adult equivalent units. This is especially important in countries where official estimates of poverty and inequality adjust for economies of scale or adult equivalence units. The sensitivity of incidence results to assumptions about economies of scale—in particular, a comparison of using per capita income or the square root scale suggested by Atkinson, Rainwater, and Smeeding (1995)—is discussed in Higgins, Lustig, Ruble, and Smeeding (2013).

#### *Missing or Zero Incomes*

When a survey respondent reports receiving a certain income source but does not report the value or reports a value of zero as their income from that source, we adopt the convention used by SEDLAC: missing and zero incomes are regarded as zero, unless the household head’s primary

---

<sup>14</sup> Note that comments in Stata are preceded by `//` or, if they are on their own line, by `*`. Comments can also be enclosed by `/*` and `*/`, but we do not use that notation here.

income source is missing or zero, in which case the household is excluded from the data (CEDLAS and World Bank, 2012). Note that when a household is excluded from the data, the expansion factors must be recalculated so that the expanded sample of the non-excluded households equals the original expanded sample size when they were included.

### *Underestimation of Beneficiaries*

The number of beneficiaries of targeted anti-poverty programs is often underestimated when compared to national accounts. For example, in Brazil, the number of beneficiary households of Bolsa Família according to the *Pesquisa de Orçamentos Familiares* is 7.3 million, compared to 12.4 million beneficiary households in 2009 according to the Ministry of Social Development. If the number of beneficiaries according to national accounts can be trusted to reflect the true number of beneficiaries (for example, if the government publishes a list of beneficiaries as in Brazil), then the program's coverage and impact will be underestimated by the survey if no correction is made.

Below we recommend a method to adjust for the underestimation of beneficiaries. The choice of whether to use the method will depend on the nature of the program and the reliability of national accounts in the country. Ideally, results should be presented both with and without the adjustment as an upper and lower bound on the number of beneficiaries. At a minimum, if the adjustment is made, an additional sensitivity analysis which shows results when this change is not made should be produced for sheets D1 (Reduction in Inequality and Poverty), D4 (Incidence by Decile and Socioeconomic Group), D5 (Concentration Shares by Decile and Socioeconomic Group), and D9 (Coverage and Leakages by Program). (This method will obviously have a large effect on the program's coverage, which is why we include sheet D9 in the tables needed "at a minimum" in this additional sensitivity analysis.)

To "impute" likely beneficiaries who did not report receiving the benefit, and match the number of beneficiaries in the survey to the number in national accounts, we follow the methodology suggested by Souza, Osorio, and Soares (2011). This method assumes that the beneficiaries who reported receiving the benefit are similar to those who did not report receiving the benefit in terms of the distributions of their incomes and characteristics; if data is available from national accounts or administrative data on the characteristics of all beneficiaries, this assumption can be checked by comparing these characteristics to the ones of the beneficiaries who reported receiving the benefit in the survey. Let the number of recipient households identified using this method be  $S$ , and the (larger) number of recipient households in national accounts be  $N$ . Finally, let the difference between the number of beneficiaries reported in national accounts and the number reported in the survey be denoted  $H \equiv N - S$ . The next step is to "identify" the  $H$  remaining beneficiary households in the survey. This is done by creating a propensity score for program participation for every household in the survey by running a probit of program participation against household income, possession of various household assets and consumer durables, number of children, race of household head, region or state, rural or urban area, etc. Then  $H$  households are randomly sampled out of the  $S$  beneficiary households, and these  $H$  beneficiary households are matched to  $H$  non-

beneficiary households with the closest propensity scores. Program benefits are then imputed to the matched households—the amount of benefit imputed is equal to the amount received (reported in the survey) by the household’s matched beneficiary household.

Note that for the above method to work it is necessary that  $H < S < N$ . It is also necessary that the probit of program participation converges, which means that the method is likely to work for targeted anti-poverty programs such as conditional cash transfers, but unlikely to work for non-targeted programs. In the case of Brazil, the probit converged for the conditional cash transfer program but not the non-contributory pension program, and was thus used for the former anti-poverty program but not the latter (see Higgins and Pereira, 2013). The researcher should also verify that the probit not only converges, but also has sufficiently high predictive power by checking the distribution of the predicted probabilities resulting from the probit.<sup>15</sup>

Sample Stata code to implement this method has been placed in [Appendix A](#).

### *Top Incomes*

It is well-known that top incomes are not well-captured by household surveys. One reason for this is that the likelihood that a household refuses to be interviewed is higher among those with top incomes. A growing literature exploits results about the statistical distribution of top incomes to adjust incidence and inequality measures to account for the exclusion of top incomes. We make no adjustments for the exclusion of top incomes in the main analysis, but an additional sensitivity analysis can be performed following the methodologies described in Box 2 and the references therein.

### **Box 2. Top incomes and inequality measurement**

*Paolo Verme, Senior Poverty Specialist in the MENA Region, World Bank*

The measurement of inequality is known to be susceptible to various statistical problems that relate to the data used for the measurement of inequality such as household income, consumption or expenditure surveys. It is known that households tend to under-report income (income under-reporting), that some households participating to the survey do not report income at all (item non-response) and that other households do not participate in surveys even when selected in the survey sample (unit non-response). These three phenomena can potentially affect the estimation of inequality seriously, although there is still incomplete evidence on the size of these

---

<sup>15</sup> A shortcoming of this procedure is that the propensity scores are estimated under the assumption that reported nonparticipants are in fact nonparticipants; however, this is not the case: the entire reason we are undertaking the analysis is that some of the reported nonparticipants must have actually been participants. We are grateful to Gary Burtless for pointing this out.

potential biases. To address the first two issues (income under-reporting and item non-response) scholars have adopted various solutions such as using consumption or expenditure in place of income or imputing income using regression techniques and a set of proxies that are known to predict income well.

The third issue (unit non-response) has only recently been studied in relation to the estimation of inequality. Preliminary findings suggest that this phenomenon can bias the estimation of inequality sharply especially when related to the right hand side of the distribution, the top incomes. Korinek, Mistiaen and Ravallion (2006) using US data have shown how household non-responses can lead to the under estimation of inequality while Cowell and Flachaire (2007) have shown how even one observation at the top of the distribution can change the estimation of inequality by several percentage points. These first findings have called for specific solutions to the problem.

Two alternative approaches have been proposed by the authors above to correct for the bias generated by unit non-responses at the top of the distribution. Korinek, Mistiaen and Ravallion (2006) propose a two-stage probabilistic model that, under certain assumptions, provides the true distribution of incomes and allows for the estimation of the correct value of inequality by using a set of weights that correct for unit non-response. Cowell and Flachaire (2007) have instead suggested estimating inequality by using a semi-parametric approach whereby inequality is estimated by combining the classic non-parametric measurement for most of the distribution with a parametric measurement applied to top incomes only. In essence, these authors suggest substituting a theoretical distribution for the top incomes- such as the Pareto distribution - which is known to predict top incomes across countries well and correcting in this way the bias at the top.

A recent paper by Hlasny and Verme (2013) proposed an alternative application of the Korinek, Mistiaen and Ravallion (2006) model and compared this application with the semi-parametric approach suggested by Cowell and Flachaire (2007). They find rather consistent results between the two approaches although the bias generated by unit non-responses among top incomes is smaller than what found by Korinek, Mistiaen and Ravallion (2006) for the US. These initial approaches proposed for correcting unit non-response at the top of the distribution are still in an experimental phase and require further tests but provide a first set of tools available to researchers.

### *Income Misreporting*

We make no adjustment for income or consumption misreporting, aside from the adjustment for underestimation of beneficiaries and optional top incomes adjustment described above.

### *Spatial Price Adjustments*

The researcher will have to use their best judgment of whether to adjust for spatial prices based on the spatial price differences in the country and the availability of a spatial price index as well as common practice in their country. Ideally, results will be presented both ways: adjusting and not adjusting for spatial price differences (one will be chosen as the benchmark and the other will be an additional sensitivity analysis).

Spatial price indices are available for many countries, either calculated by the government itself or by an international organization. If an adjustment is made for spatial price differences, a table should be provided showing the value of the spatial price index (SPI) in each region. Note that the choice of which region was used to index the SPI may have been arbitrary. Hence, you should re-index your spatial price index so that 1.0 equals its weighted average. Consider the following simple example, where the original spatial price index was indexed to the country's federal district.

Region	Population share	Original SPI
Federal District	55%	1.000
Urban Interior	15%	0.750
Rural Interior	30%	0.600

We would re-index the SPI as follows: first, compute its weighted average as  $(0.55 \times 1.000 + 0.15 \times 0.750 + 0.30 \times 0.600) = 0.8425$ . Next, divide the original SPI by its weighted average to create a re-indexed SPI.

Region	Population share	Original SPI	Calculation	Re-indexed
Federal District	55%	1.000	$1.000/0.8425$	1.1869
Urban Interior	15%	0.750	$0.750/0.8425$	0.8902
Rural Interior	30%	0.600	$0.600/0.8425$	0.7122
<i>Weighted Average</i>		<i>0.8425</i>		<i>1.0000</i>

Finally, all of the income concepts and the variables for each of their components should be adjusted for spatial prices, by dividing the value of those variables by the re-indexed value of the SPI corresponding to a particular household's region. (To see why re-indexing was necessary, note that the above "Original SPI" could have instead been arbitrarily indexed to the rural interior, so that it was Federal District 1.667; Urban Interior 1.250; Rural Interior 1.000. Dividing incomes by the 1.667; 1.250; 1.000 index instead of the 1.000; 0.750; 0.600 index—which tell the exact same story about price differences—would have large implications for poverty. Hence, we re-index for consistency.)

If a reliable spatial price index is not available, an alternative is to create a spatial price index using spatial poverty lines, which again might have been calculated by the government or an international organization. This solution is not ideal, since the poverty lines are calculated based on the prices of basic needs, while the prices of other goods may not differ across regions in the same way as basic

needs. Nevertheless, it is better than making no adjustment for the differences in purchasing power experienced by individuals in different regions. Consider the following example.

Region	Population share	Regional poverty line
Federal District	55%	320 local currency per month
Urban Interior	15%	250 local currency per month
Rural Interior	30%	190 local currency per month

Treating the regional poverty lines as a (non-indexed) SPI, we calculate the re-indexed SPI the same way: compute its weighted average as  $0.55 \cdot 320 + 0.15 \cdot 250 + 0.30 \cdot 190 = 270.5$ , and divide the original SPI (that is, the regional poverty lines) by the weighted average to obtain the re-indexed SPI.

Region	Population share	Regional poverty lines	Calculation	Re-indexed
Federal District	55%	320	$320/270.5$	1.1830
Urban Interior	15%	250	$250/270.5$	0.9242
Rural Interior	30%	190	$190/270.5$	0.7024
<i>Weighted Average</i>		<i>270.5</i>		<i>1.0000</i>

### *General Equilibrium and Behavioral Effects*

At this point, CEQ only considers first-order effects (also known as partial equilibrium analysis). We do not account for behavioral or general equilibrium (GE) effects, although it is worth noting that our economic incidence assumptions (for example, on who bears the burden of payroll or consumption taxes) are based on GE theory. In essence, one assumes zero demand price and labor supply elasticities and zero elasticities of substitution among inputs, which may not be far-fetched assumptions for analyzing effects in the short-run. As Coady et al. (2006, p. 9) put it: “The first order estimate is much easier to calculate, provides a bound on the real-income effect, and is likely to closely approximate a more sophisticated estimate. Finally, since one expects that short-run substitution elasticities are smaller than long-run elasticities, the first-order estimate will be a better approximation of the short-run welfare impact.”

It is important to note, however, that the first-order effects *do* take into account both the direct effects of indirect taxes and subsidies as well as the indirect effects on final goods’ prices of indirect taxes and subsidies on inputs. For the latter one uses input-output matrices, described below and also in Coady et al., for example. Indirect effects should not be confused with GE effects because the indirect effects measured with input-output tables still do not incorporate behavioral responses to changes in relative prices.

If a team decides to depart from partial equilibrium analysis, it should be carefully explained and done as an additional sensitivity analysis so that the benchmark results can still be compared with those for other countries. If the researcher is interested, for work on incidence analysis accounting for behavioral effects, see, for example, Coady (2006) and Ravallion and Chen (2013).



### *Intertemporal Effects and Lifetime Incidence*

CEQ analyzes cross-sectional data and thus provides a point-in-time perspective on the incidence of taxation and social spending. While some work has focused on intertemporal effects and lifetime tax incidence, we do not due to data limitations. In particular, “the lifetime perspective requires much more data over long periods of time, because results depend critically on the whole shape of the lifetime earnings profile” (Fullerton and Rogers, 1991, p. 277). Compared to a lifetime perspective, we are therefore likely overstating the progressivity of income taxes and the regressivity of consumption taxes. We take some solace in that Slemrod (1992) finds that replacing annual income with a longer-term income average did not significantly reduce the measured degree of inequality in the U.S., and Fullerton and Rogers (1991) find that “the lifetime incidence of the entire U.S. tax system is strikingly similar to the annual incidence” (p. 277).

### *Spillover Effects*

CEQ does not incorporate spillover effects due to the difficulty in estimating their magnitudes and the beneficiaries. For estimates of the spillover effects of cash transfer programs, see Barrientos and Sabates-Wheeler (2009) and Angelucci and De Giorgi (2009).

## **v. Benchmark Case and Sensitivity Analyses**

As mentioned above, there is no agreement on whether to consider contributory social security pensions as part of market income or as a government transfer. Hence, we opted for doing it both ways to check how sensitive results to the treatment of contributory pensions are. We define a benchmark case in which contributory pensions are part of market income. We also do a sensitivity analysis where pensions are classified under government transfers. Other sensitivity analysis will be country-specific (i.e., some countries may want to check the implications of adjusting for the underreporting of beneficiaries of a transfer program, using different methods to impute a subsidy, making different assumptions about consumption tax evasion, etc.). Additional sensitivity analyses can be added by copying and inserting additional sets of tables in the Master Workbook; make sure to clearly describe each sensitivity analysis. While it is ideal to reproduce results in section D for every “additional” sensitivity analysis, this is only required for Sensitivity Analysis 1. At a minimum, the results from sheets D1, D4, and D5 should be reproduced to enable a preliminary analysis of the sensitivity of results to the alternate methods being considered. Details of the benchmark case and sensitivity analysis are as follows.

### *Benchmark Case*

As mentioned under the definitions of income, all pensions except pensions received from the non-contributory system should be included in market income. Pensions received from the non-contributory system (sometimes called “minimum pensions”) are social assistance, thus they are not included in market income in the benchmark case; they are treated as a government transfer.

Including all pensions except those from the non-contributory system as part of market income is a simplification. In countries with a “pay-as-you-go” pension system, employee and employer contributions into the social security system can be smaller than the amount paid out by the system, which results in a social security deficit that is financed by the government. In this case, a portion of pensions should technically be considered a subsidy; however, there is no way to identify from the household surveys whose pensions are coming from the subsidized portion of the social security system, and whose pensions are coming from the contributory pool. As a result, all pensions except those from the non-contributory system will be considered part of market income in the benchmark case.

Since we are considering pensions a form of intertemporal savings, we do not subtract contributions to the social security system that are directed to pensions from income when moving from market to net market income in the benchmark case. (In the case where income reported on the survey is net of contributions directed to pensions, the latter must be imputed and added into income.) We do subtract out direct taxes and contributions that are not directed to pensions.

#### *Sensitivity Analysis 1*

The main sensitivity analysis is to treat social security pensions as a government transfer. Thus they are not included in market or net market income. Contributions to social security directed to pensions are subtracted out of income when moving from net market income to disposable income in the sensitivity analysis. As a result, the benchmark case disposable income and sensitivity analysis disposable income are slightly different, even though in both cases contributory pensions have been added in by this point: the difference is that in the benchmark case contributions directed to pensions are never subtracted out of income so they are included in benchmark case disposable income.

#### *Additional Sensitivity Analyses*

Throughout this Handbook, we recommend situations in which it is recommended or optional to perform additional sensitivity analyses. We have created space in Section D of the Master Workbook for the presentation of results from the first of these additional sensitivity analyses, which would be numbered Sensitivity Analysis 2. The results from additional sensitivity analyses can be added by copying and inserting additional sets of tables in the Master Workbook and numbering them consecutively as Sensitivity Analysis 3, etc. The more sensitivity analyses the better, as it shows where our main results are robust and where they are not.

## **vi. Constructing Market Income**

Market income begins with gross (pre-tax) wages and salaries from the formal and informal sectors (also known as earned income) and income from capital (rents, profits, dividends, interest, and so on). It also includes private transfers (remittances and other private transfers such as alimony), imputed rent for owner occupied housing; also known as income from owner occupied housing and the value of own production. When using income as the welfare aggregate, most of these components can be directly extracted from the household survey data; additional methodological details are discussed below. We do not include extraordinary income from the sale of durables, irregular gifts, etc.

In the benchmark case, market income also includes retirement pensions from the contributory social security system. In Sensitivity Analysis 1, they are included under government transfers. For treatment of contributory pensions paid as a lump sum see Box 3.

### **Box 3. Contributory Pensions Paid as a Lump-sum**

In the case of lump-sum pensions (i.e., an individual is paid a large sum upon retiring and nothing thereafter, rather than a smaller pension annually), this pension is extraordinary income and cannot all be counted in income for that year. The following includes proposals whose methodological soundness is still subject to review so the researcher should exercise caution in applying them.

If the survey contains a question about who is a pensioner (i.e., who received the lump sum pension at some point in the past), total spending on pensions by the government that year (scaled-down with the same method applied to education and health described below) should be divided by the number of pensioners identified in the survey (expanded using expansion weights, of course) to estimate the per pensioner benefit, which would then be imputed to those identified as pensioners. If the survey does not contain a question about who is a pensioner, the program could be simulated based on its rules. The researcher would simulate who has received the lump-sum pension in the past, and divide the total spent by the government in that year on pensions (scaled-down with the same method applied to education and health described below) among those individuals identified as pensioners.

If neither of these is possible in a country with lump-sum pensions, the researcher could include the lump-sum pensions as reported in the survey and divide them by the number of years between the average age when the lump-sum pension is received and the average life expectancy. Of course, this will underestimate income from lump-sum pensions because only those who received them in the years of the survey—and not those who had received them in previous years—would be included. If more than one of these options are available, it is advisable to perform one or more additional sensitivity analyses to see if results are robust to the different methods.

Sometimes, the questions in the survey force the researcher to start at *net market income* and work backwards: for example, if the questions about income are net of taxes, one should construct net market income with data observed in the survey, then “work backwards” and simulate the tax code to arrive at market income.

When consumption is chosen, for example because income data is unavailable or unreliable, as mentioned above we equate consumption to disposable “income”, and then work backwards (i.e. subtract out transfers) to get to net market “income.” We then proceed to calculate market income following the procedure described in the paragraph immediately above.

### *Grossing up*

Grossing up is the terminology used to explain how to calculate market income of, for example, wage earners given the assumption that the economic incidence of payroll taxes paid by employers (known as employers’ contributions as well) also falls on wage earners in the form of lower market wages. In essence, we are assuming that in the absence of employers’ contributions, the market wages would have been higher by the amount of these contributions. In the surveys, reported wage income is net of these taxes (compared to the counterfactual in which the tax didn’t exist and the employer paid that additional income to the worker). Hence, market income must be *grossed up* by the amount paid in the tax, so that when the tax is subtracted out when moving from market to net market income, we arrive back at income net of direct taxes.

As a simple example, suppose employers in the formal sector must pay  $x\%$  of the employee’s gross wage as a payroll tax. The amount of the payroll tax is calculated as  $x\%$  of the employee’s net reported wages divided by  $(1 - (x/100))$  because the latter equals gross wages, and this amount is *added* to the individual’s wage income to arrive at a counter-factual pre-employer payroll tax wage income. This process is known as “grossing up” because one needs to gross-up ‘observed’ market income. This counter-factual pre-employer payroll tax wage income is used in the market income aggregate. More concretely, suppose an individual reports wage income from the formal sector of \$100 (gross of any taxes or contributions paid by the employee), individual income taxes paid of \$10, and non-wage sources of market totaling \$20. If the employer-paid payroll tax were not considered, we would have market income = \$120, direct taxes = \$10, net market income = \$110. If we now consider a payroll tax paid by the employer of \$8 on the employee’s income gross of any taxes paid by the employee (in this case, we have pre-payroll tax counterfactual wage income = \$108 and direct taxes = \$10 + \$8 = \$18. This gives market income = \$128, direct taxes = \$18, and as before net market income = \$110. Grossing up should also be performed for property taxes and (if they are included in an additional sensitivity analysis) for corporate income taxes.

Some surveys include questions on the amounts paid in taxes on extraordinary income such as inheritance. In this case, it is desirable to include that tax in the analysis since the data is available and we might otherwise be missing a highly progressive tax in our analysis. However, since the extraordinary income was not included in income, while the tax is presumably paid out of that extraordinary income rather than the individual's annual income stream, this is another instance in which market income must be *grossed up*: the amount paid in inheritance tax would be added into market income (and subtracted back out when moving from market to net market income).<sup>16</sup>

#### *Negative farm, business, and self-employed incomes*

In some surveys, farm, business, and self-employment incomes can be reported as negative numbers if the interviewee's business suffered a loss during the reference period. Leaving negative incomes in the data complicates the interpretation of results for many of our measures (for example, imagine trying to draw a Lorenz curve if income for some observations is negative). Hence, we adopt the following convention: the particular variable that has a negative value (for example, farm income) is left as negative, but if total market income ends up being negative once all income components are aggregated at the household level, then that negative market income is converted to zero. The researcher should report the proportion of the sample which had negative market income that was then converted to zero.<sup>17</sup>

#### *Top coding*

In some surveys, wage and other income variables are top-coded for very high earners to protect the privacy of respondents. The simplest approach available to replace the top coded value for that variable--which must be done as a precursor to creating any income concepts--is to replace the top coded values with either the lower bound of the top coding or the maximum non-top coded value, whichever is available. For example, survey might inform us that every income above \$100,000 has been top coded; in this case, we use the *lower bound of the top coding* which is \$100,000 for all the households whose income was subjected to top coding. Alternatively, some surveys (such as the Current Population Survey in the US) do not report what the cut-off for top coding is, but simply inform us that all observations that have a value for that variable of, say, 999999, are top coded. In this case, we find the maximum of the non-top coded observations (in this example, the observations with a value below 999999 for that variable) and assign it to all of the top-coded variables. For example, suppose the codebook accompanying our household survey data says that 999999 indicates a top coded value, but does not provide us with information about what income level was used as the cut-off for top coding. We check our data and find that the highest value for the corresponding variable that is below 999999 is \$585,400. For all households whose income was subject to top-coding, we would assign them with the *maximum non-top coded value* which is \$585,400.

---

<sup>16</sup> We are grateful to Jorge Martinez-Vazquez for feedback on how to treat taxes on extraordinary income.

<sup>17</sup> We are grateful to David Phillips for confirming that this is the method used by the UK in its household income statistics.

If this approach is taken and multiple years or multiple countries are being compared by the same authors, an adjustment should be made to account for the fact that the top-coding cut-off may be arbitrary and could thus occur at different points of the variable's distribution in the different surveys. Box 4 describes how to adjust the top coding in a way that it becomes comparable across years or countries.

**Box 4. Top coding across multiple years or countries**

*Gary Burtless, Senior Fellow and John C. and Nancy D. Whitehead Chair,  
Brookings Institution*

To make cross-year or cross-country comparisons comparable, calculate the lowest percentile in the income distribution that the top-code value represents in all of the years or countries being studied. Then, use this top code percentile to top code each of the years or countries at the same percentile. For example, suppose the top-code value is at the 97th percentile in year or country 1, the 98th percentile in year or country 2, and the 96th percentile in year or country 3. Create a new, uniform top-code at the 96th percentile in each of the years or countries. In year or country 1, every respondent with an income value above the 96th percentile is assigned a top-code equal to the 96th percentile of the income distribution in year or country 1; and in year or country 2, every respondent with an income value above the 96th percentile is assigned a top code equal to the 96th percentile of the income distribution in year or country 2. The top codes for year or country 3 are left unchanged since that year or country had the lowest percentile at which top coding occurred. This procedure ignores information about incomes between the 96th and 97th percentile in year or country 1 and between the 96th and 98th percentiles in year or country 2, but the top code procedure makes it feasible to evenhandedly compare income distributions and fiscal incidence across the three years.

More complex approaches involve imputing values to the top-coded values. (Note that if values are imputed, the methods described in the above box for analyses across multiple years or countries are no longer necessary.) If income and consumption data are both available in the survey, a regression using consumption and other characteristics as explanatory variables can be used to predict the missing income component. Alternatively, the top coded values could be imputed using assumptions about the distribution of income at the upper end (for example, that it follows a Pareto distribution—see Box 2). A more complex multiple imputation approach is given in Jenkins et al. (2011).

The method chosen in the event of top coding must be made based on the nature of the top coding in the data set and the researchers' preference to employ simpler or more complex solutions. The



reasoning behind choosing a particular methodology should always be justified, and ideally, the sensitivity of results to the chosen method should be tested.

### *Imputed Rent for Owner Occupied Housing*

There are multiple methodologies to impute the value of owner-occupied housing. In some countries, survey questionnaires ask families who own their homes to report the amount they think they would be paying in rent for the same dwelling, or for how much they would rent it out. In the case where there is no such question, or if the authors feel that survey respondents do not have sufficient information about housing markets to answer this question accurately, the regression methodology described below can be used instead. A minimal check of the accuracy of self-reported rental values could be to compare the mean of this variable to the mean predicted rent that is obtained from the regression methodology described below.

A standard methodology uses a regression to impute the value of owner-occupied housing. This requires that the survey contains information on how much renters pay per month in rent. For the subset of households that rent, (the log of) their monthly rent is the dependent variable in the regression. Potential independent variables include any characteristics about the dwelling, as well as income per capita of the household. See Appendix C for a detailed example. For instance, after exploring a number of potential independent variables, we end up using the following variables for the case of Brazil: number of bedrooms, number of bathrooms, log household income per capita, rural dummy, state dummies, interaction terms between state dummies and the rural dummy, sets of dummies for whether the dwelling is a house, apartment, or room in a shared building, the material of the walls, type of sewage, presence of piped water, floor material, roofing material, and an intercept. Alternatively, Paz Arauco et al. (2013) perform three separate regressions for houses, apartments, and other housing types, using similar dependent variables as those described in Appendix C. The estimated vector of coefficients for households who are renters of their home, is then applied to those variables for owner-occupiers. This generates a predicted rental value for owner occupiers. If you use the regression methodology, describe your variable selection process (see Appendix C for an example) and provide the regression results in the Master Workbook Template on the sheet titled Valuation of Imputed Rent for Owner's Occupied Housing and Autoconsumption, in the Methodological Aspects and Assumptions section.

The first method requires a response to a survey question about the value of owner-occupied housing, while the second method requires that families who rent their dwellings report how much they pay in rent. If neither piece of information is available, we resort to the methodology used by SEDLAC for countries in this scenario, which only requires a question as to whether households rent their homes. By this methodology, the incomes of families who own their own homes is increased by 10%, which according to SEDLAC is a value that is “consistent with estimates of implicit rents in the region” (CEDLAS and World Bank, 2012, p.18).

### *Self-consumption*

The method used to determine the value of self-consumption (i.e., production for own consumption) depends on the survey data available. Surveys with consumption data often ask whether that item was produced or purchased. The value of items that were produced by the household, taken from the household's own business inventory, or donated to the household (by someone other than the government) are included in market income as production for own consumption. Other surveys simply ask one or more questions about the total value of production for own consumption; in that case this value is added to market income. The researcher should perform a sensitivity analysis testing results both including and excluding the value of production for own consumption in the definition of income and make sure that the results including the value of production for own consumption make sense. As an example, including the value of production for own consumption in the case of Bolivia led poverty rates to be lower than in Mexico (a country with a GDP per capita roughly three times higher than Bolivia), which led us to believe that this variable was flawed and should not be used in our income aggregates.

When no variable is available to estimate production for own consumption, it will simply not be included in income.

## **vii. Constructing Net Market Income**

Start from market income if the survey contains information on gross wages. Then, subtract direct taxes and contributions—as explained below—to arrive at net market income... Alternatively, one might start with net market income (because, for example, incomes in the survey are reported net of taxes) and work backwards to construct market income, or—if using consumption data—start with disposable “income” and work backwards to net market and then market income. Regardless of where you start, net market income is net of direct taxes and contributions to social security.

### *Direct Taxes*

Direct taxes are personal income taxes, payroll taxes (paid by both the employer and employee, net of payroll taxes that go to the contributory pension system in the benchmark case), and property taxes. Corporate taxes and other forms of direct taxes that are not captured by the household survey and not able to be simulated are not included in this analysis.<sup>18</sup> When personal income taxes are not reported in the survey, they should be simulated based on the prevailing tax code and tax evasion assumptions. When tax incidence is obtained by the simulation method, the latter should be described with detail, including the evasion assumptions. As a last resort, the incidence of taxes could be obtained from other studies on tax incidence for the same country.

---

<sup>18</sup> For countries that are able to simulate the corporate income tax, the burden of corporate income taxes is assumed to fall entirely on capital income. It is also assumed that all financial assets (not just corporate stock) bear the tax equally. See Piketty and Saez (2007).

The burden of personal income taxes is assumed to fall entirely on labor in the formal sector, in the form of reduced wages. In other words, if a survey reports gross wages and the amount paid in taxes, the reported amount paid in taxes is subtracted in full from pre-tax income. If the survey reports net wages and the amount paid in taxes, gross wages are obtained by “working backwards” and adding the amount paid in taxes to net wages to obtain gross wages. The burden of payroll taxes is assumed to be borne fully by labor in the formal sector, again recalling that market income must be *grossed up* to create the pre-payroll tax counterfactual (and the grossing-up for benchmark and sensitivity analysis 1 should follow the same approach as that for the payroll taxes paid by employees in terms of when to include contributions to old-age pensions).

The burden of property taxes is assumed to fall entirely on the holders of property. If there is a survey question on property taxes paid, we use this information and assume that the tax is borne by those who reported paying it in the survey. (Note that the amount of property taxes paid might be found in the consumption module of surveys that include consumption.) If there is no question on property taxes paid, information on who is a property owner and the value of their property can be used in combination with knowledge of the tax code, again assuming that the tax is borne fully by owners of property. If information about the value of the property is not available, the researcher will have to assess whether he or she has enough information on property ownership to simulate the tax.

Note that the base income for any tax simulations should always *exclude* non-taxable income, which includes but is not limited to the income we are imputing for owner occupied housing, production for own consumption, non-taxable fringe benefits, and the value of grossing up for any taxes that the individual did not pay but are assumed to be borne by the individual (for example, payroll taxes paid by employers).

### *Contributions to Social Security*

As discussed in the above section, contributions to social security are treated as follows:

Benchmark case: Because we are considering pensions a form of intertemporal savings, we do not subtract contributions to the social security system that are directed to pensions from income when moving from market to net market income in the benchmark case. (In the case where income reported on the survey is net of contributions directed to pensions, the latter must be imputed and added into market income.) We do subtract out contributions that are not directed to pensions.

Sensitivity Analysis 1: Contributions to social security directed to pensions are subtracted out of income when moving from net market income to disposable income in the sensitivity analysis. As a result, benchmark case disposable income and sensitivity analysis disposable income are slightly different, even though in both case contributory pensions have been added in by this point: the difference is that in the benchmark case contributions directed to

pensions are never subtracted out of income so they are included in benchmark case disposable income.

If your survey reports disposable income (i.e., income that already includes direct transfers), work backwards to net market income by subtracting direct transfers out.

Remember that when consumption is used instead of income (because income data is unavailable or unreliable), consumption is taken to mean disposable income, and then work backwards (i.e. subtract out transfers) to get to net market income. To get net market income, you must subtract direct transfers in the same way you would do it if your survey would report disposable income itself.

### **viii. Constructing Disposable Income**

If using an income-based survey and the reported income variable is disposable income (i.e., income net of direct taxes and including government direct transfers), just use the values directly. If using a consumption-based survey, just use the consumption values as if they were equal to disposable income. If the survey reports net market income, to construct disposable income add direct government transfers. In Sensitivity Analysis 1, also add contributory pensions (because by construction you should not have included them in market income as you do in the benchmark case).

#### *Add Direct Government Transfers*

Direct government transfers includes, but is not limited to, conditional cash transfer programs, non-contributory pensions, scholarships, public works programs, and other direct transfers (which may or may not be targeted to the poor). In the case of public works programs (also known as pay for work or welfare to work programs), we include the full value of wages paid in these programs as direct transfers and do not attempt to subtract the opportunity cost of the individual's time in the Benchmark Case or Sensitivity Analysis 1; the researcher may wish to perform an additional sensitivity analysis in which they do estimate and subtract opportunity cost. Food transfers, although not cash, are considered a direct transfer because they have a well-defined market value and are close substitutes for cash. Similarly, school scholarships, school uniforms, and other near-cash benefits are treated as direct government government transfers. Unemployment benefits and other benefits that might be part of the contributory system but are intended to deal with idiosyncratic shocks are also counted as direct transfers (and should therefore not be included in social security pensions which are part of market income in the benchmark case).

#### *Contributory Pensions in Sensitivity Analysis 1 ONLY*

In Sensitivity Analysis 1, contributory pensions were not a component of market income and are considered a government transfer, and are thus added into income when moving from net market to disposable income and for the incidence analysis they are treated as any other direct transfer.

## ix. Constructing Post-fiscal Income

From disposable income (or consumption if you are using a consumption-based survey), subtract indirect taxes and add indirect subsidies.

### *Subtract Indirect Taxes*

The burden of indirect taxes is assumed to fall entirely on the consumer in the form of increased prices. Strictly speaking this assumption should only be applied to nontradeable goods. If you wish to introduce a distinction between the effect of indirect taxes on tradeable and nontradeable goods, follow the methodology discussed in Coady (2006). When the survey being used contains both income and consumption data or consumption data only (or an income-only survey is being used in conjunction with a consumption survey and a matching technique to generate consumption totals by category of consumption good for each household in the income-only survey), indirect taxes should be simulated using consumption—not income—data.

Tax rates for the prevailing indirect taxes (such as consumption taxes in the form of a value-added tax) are applied to each household's reported consumption of the corresponding items. Because indirect taxes can apply to both final consumption goods and services and inputs, an input-output (IO) table should be used to determine the indirect impact of taxes on inputs on the prices of final consumption goods. For details, see Coady et al. (2006), for example.

However, due to tax evasion or informality, which are widespread in developing countries, consumers in rural areas and those who purchase from informal sellers (e.g., street vendors, farmers' markets, and so on—when the survey contains a question about place of purchase) might not directly pay indirect taxes. Rajemison, Haggblade, and Younger (2003) show that using statutory rates can overestimate the impact of indirect taxes on incomes. Where estimates are available or can be calculated, effective tax rates reflecting the rates paid in reality—rather than the legal rates, which overestimate actual collection of indirect taxes—should be used.

A simple option is to assume that people living in rural areas or who purchase from informal sellers do not pay consumption taxes. However, even if they might not directly pay indirect (consumption) taxes, they cannot be assumed to have paid no indirect tax because of the indirect effects of indirect taxes on inputs. Hence, an IO table should be used. For details, see Coady et al. (2006) and Coady (2006). Goods that are exempt from consumption taxes should also include the indirect effects of indirect taxes on inputs, again computed using an IO table. Only goods that are taxed at zero-rate can be assumed to involve no indirect taxes since producers are reimbursed for any taxes paid on their inputs.

Once effective rates for different groups of consumption goods have been calculated using an IO table or obtained from a secondary source, the next step depends on the type of survey data available—in particular, whether the survey has consumption data only or both consumption and

income data. (The latter also includes income-only surveys if they are matched with a consumption survey to generate consumption totals by category for each household.) In either case, suppose that consumption goods have been divided into  $K$  groups, with tax rates  $t_k$  and denote the post-tax price of consumption category  $k$  by household  $i$  as  $c_k$ .

For a survey with consumption data only (or income and consumption data when consumption is being used as the measure of well-being), the total amount spent on indirect taxes is calculated as  $\text{IndT} = \sum_{k=1}^K t_k c_k$  and this amount is subtracted from total consumption when moving from “disposable income” (that is, consumption) to post-fiscal “income.”

For a survey with income and consumption data (or where consumption by category is generated by matching with an alternate survey) when income is being used as the measure of well-being, subtracting  $\sum_{k=1}^K t_k c_k$  from income when moving from disposable income would be problematic for two reasons. First, we would be measuring the incidence of *consumption* taxes as a percent of income, which could make them appear regressive even if their incidence is progressive when measured as a percent of consumption.<sup>19</sup> Second, some observations in household survey microdata have reported consumption that is much higher than reported income, either due to underreporting of income, dissaving, or borrowing. Some of the households with consumption much higher than reported income end up with negative post-fiscal income if we simply subtract  $\sum_{k=1}^K t_k c_k$  from disposable income. Thus, for a survey with income and consumption data when income is being used as the measure of well-being, we follow IDB (2009) and estimate indirect taxes as

$$\text{IndT} = \frac{\sum_{k=1}^K t_k c_k}{\sum_{k=1}^K c_k} \times y^d$$

where  $y^d$  denotes disposable income.

For example, suppose there are two goods: bread and milk. The effective tax rate on bread is 5% and on milk is 10%. A household at the lower end of the income distribution has reported disposable income of \$10, reported consumption of bread as \$8, and reported consumption of milk of \$12. Reported consumption exceeds reported income, which often occurs at the lower end of the distribution, perhaps because the household is borrowing or dissaving to meet its consumption needs or perhaps because of errors in reporting one of them. Rather than computing indirect taxes as  $.05 \times 8 + .10 \times 12 = \$1.60$ , and calculate the rate of paid indirect taxes as  $\$1.60 / \$10$  and hence state that the household pays 16% of its income in indirect taxes (which is higher than the effective tax rate for both bread and milk!), we would calculate the percent of *consumption* paid in indirect taxes as  $(.05 \times 8 + .10 \times 12) / (8 + 12) = 0.08$  (i.e., 8%) and then multiply this by disposable income to arrive at

---

<sup>19</sup> We thank David Phillips for his feedback on this issue.

total indirect taxes paid of  $0.08 \times 10 = \$0.80$ . Although this is not the *actual* amount of indirect taxes paid, it allows us to correctly estimate the progressivity of indirect taxes.

When the survey has income data only, secondary sources may be used. For example, a secondary source might provide the percent of consumption spent on indirect taxes by consumption decile. (Note that for the same reasons discussed above, the secondary source should give the percent of consumption spent on indirect taxes, not the percent of income spent on indirect taxes.) This percent by decile is then applied to the disposable income of each individual in the corresponding *consumption* decile (not income decile; this may require calculating a new variable that denote's each households placement in the distribution of consumption) from the CEQ analysis to obtain her spending on indirect taxes. The implicit assumption being made when one uses indirect taxes by consumption decile is that everyone in that consumption decile pays the same proportion of their consumption (equal to the average over the decile) in indirect taxes.

### *Add Indirect Subsidies*

Indirect subsidies can be on final consumption goods and services or on inputs. Consumption subsidies of a fixed percentage can be measured in the same way as consumption taxes described above. Price subsidies on inputs will be passed on to consumers through the cost structure of final consumption goods, both directly and indirectly, which is why we use an IO matrix to measure their impacts on the prices of final goods. Distinctions between tradeables and nontradeables are analogous as well. More details for specific types of subsidies are given below.

#### *Fuel subsidies*

If the government subsidizes petroleum products, the incidence of these subsidies should be estimated and their value should be added into income when moving from disposable to post-fiscal income. In many cases, the indirect effects of fuel subsidies (through their effect on the prices of goods for which fuel is an input) are larger than the direct effects (Coady et al., 2006), so they should be included in the analysis.

The first step to calculating both the direct and indirect effects is to figure out the magnitude of the price subsidy. This requires estimating what the price would be in the absence of the subsidy. If the government fixes the subsidy as a set percentage of market price, then this is straight-forward. If, on the other hand, the government sets a price control—either by controlling import levels, domestic distribution, and domestic prices, or by leaving importing and distributing to the private sector but setting domestic price ceilings and compensating domestic distributors for resulting losses—the market domestic price in the absence of the subsidy must be determined.

Following Coady et al. (2006, Appendix I), there are three possible “reference prices,” or prices in the absence of the subsidy. The export price  $p^x$  equals the world price minus the cost of transportation to the border. The import price  $p^m$  equals the world price plus the

cost of transportation to the country's border. Finally, the country could choose not to participate in trade, in which case the price in the absence of the subsidy will equal the marginal cost of production at the equilibrium quantity that would be demanded in the absence of the subsidy; since this price is a function of the quantity demanded, we write it as  $p^d(q^*)$ . Choosing the correct reference price depends on the relationship between these three prices. If  $p^m > p^x > p^d(q^*)$ , the country could profitably export in the absence of the subsidy, so the export price should be chosen as the reference price. If  $p^m \geq p^d(q^*) \geq p^x$ , the country would not import or export in the absence of the subsidy and the marginal cost of production at the quantity that would be demanded in the absence of the subsidy is the appropriate reference point. Finally, if  $p^d(q^*) > p^m > p^x$ , the country would import in the absence of the subsidy and the import price is the appropriate reference price.

Once the reference price has been determined, and assuming that subsidies are fully passed through to consumers, the direct effect can be easily computed. Denoting the reference price as  $p^0$  and the subsidized price  $p^s$ , the direct benefit from the subsidy for individual  $i$  is equal to the quantity of the good he or she consumes multiplied by the size of the subsidy,  $p^0 - p^s$ .

Since petroleum products are used as an input in the production of many other goods, a subsidy on their price will also impact the prices of other consumer goods. These indirect effects are often larger than the direct effects of the fuel subsidy (Coady et al., 2006; Arze del Granado, Coady, and Gillingham, 2012), and can be estimated by using input-output (IO) tables.

An IO table (or matrix) represents the inter-dependencies between different sectors of an economy. The rows of the table represents each sector's outputs, while each column represents each sector's inputs. If an IO table is available from a reasonably recent year for the country, it can be used to estimate the indirect effects of a fuel subsidy. In the absence of a very recent IO table, we prefer using an older IO table from the country being analyzed to the alternative of using an IO table from a country with a "similar" economy; however, the choice will depend on the judgment of the researcher. If an IO table from the country being studied is not available, indirect effects can be estimated using average indirect effects across twenty countries calculated in the meta-analysis Arze del Granado, Coady, and Gillingham (2012). If the different sections of the fuel sector (e.g., kerosene, liquefied gas, gasoline) are grouped together, they should be separated out. The indirect benefits of the price subsidy can be measured by simulating a price increase in the IO table from  $p^s$  to  $p^0$ . Sample Stata code for this is included below, where we assume that the IO table is saved as a tab-delimited text file which we will call `iotable.txt`; if it saved as another format, see `help insheet`.



In the example below, suppose we calculated that the elimination of the subsidy would increase the price of kerosene by 94%, the price of petrol and diesel by 33%, and the price of electricity by one third of the diesel and petrol price increase. Further, suppose that kerosene is sector 29 in the IO table, petrol and diesel sector 30, and electricity sector 31.

The Stata code below is adapted from code provided to the authors by the Fiscal Affairs department at the International Monetary Fund.

```
* first, load the IO table
clear // if necessary, save your data first
insheet using iotable.txt
mkmat *, matrix(A) // puts IO table in a matrix
local Nsectors = rowsof(A) // number of sectors

* specify price changes (calculated as precursor to this analysis)
local fixprice "29 30 31"
local dpkero = 0.94 // price change in kerosene
local dpother = 0.33 // price change in petrol and diesel
local dpelec = `dpother'*(1/3) // assume elec price increase is 1/3 of
                             // diesel and petrol price increase

* vector for simulated price changes
matrix dp_sim = J(1, `Nsectors', 0)
matrix dp_sim[1, 29] = `dpkero'
matrix dp_sim[1, 30] = `dpother'
matrix dp_sim[1, 31] = `dpelec'

* specify row/column numbers of the commodities whose prices will be
* fixed
matrix gamma = J(`Nsectors', `Nsectors', 0) // fixed price matrix
foreach petrolrow of numlist `fixprice' {
    matrix gamma[`petrolrow', `petrolrow'] = 1
}

* calculating cost-push model pass-through for prices of all sectors
matrix alpha = I(`Nsectors') - gamma
matrix V = inv(I(`Nsectors') - alpha*A)
matrix deltaptilda = dp_sim*A*V

* output simulated price shock and price pass-through on all sectors
display "indirect effect price increase"
matrix list deltaptilda
```

Now, the indirect benefits of the subsidy for household  $i$  are calculated as the indirect effect price increase in sector  $j$  (displayed in column  $j$  of the row vector `deltaptilda`) multiplied by the amount spent on goods in sector  $j$  by household  $i$ .

*Household energy subsidies*

In some countries, the government directly subsidizes electricity prices for households who consume low enough amounts of energy, often using an inverted block tariff (IBT) structure. When these subsidies are provided for household energy consumption only, estimating the first-order direct effects is sufficient. Consider the example of Brazil, where the Social Tariff on Electric Energy (TSEE) is an IBT price subsidy on energy. In 2009, eligible households consuming less than 30 kWh per month received a 65 percent discount, households consuming over 30 but less than 100 kWh received a 40 percent discount, and households consuming between 100 kWh and 220 kWh received a 10 percent discount; households consuming more than 220 kWh were charged market price.<sup>20</sup> Note that inverted block tariffs can also require household consuming above a certain amount to pay *higher* than market price, to cross-subsidize those who are paying below market price. In this case, the amount each household pays above market price should be calculated using the same method as described below, and treated as an indirect tax.

If the survey provides data on the total kilowatt hours consumed by the household, then it is straight-forward to classify each household by their consumption level, which determines the proportional subsidy they receive according to the tariff rule. Then, we multiply this proportional subsidy by the amount they spent on electric energy to get the value of the subsidy. If, however, the survey provides data on the total spent on electricity but not the total kilowatt hours consumed, the latter must be calculated. We will illustrate with an example from Brazil. Denote the market price of electricity as  $\$p$  per kWh. If households consuming less than 30 kWh per month receive a 65% discount as in Brazil, then any household spending less than  $(1 - 0.65) * 30p$  a month on electricity would be assumed to have received the 65% subsidy. Suppose the household reported spending  $c < (1 - 0.65) * 30p$  for the month; the direct effect of the subsidy (i.e., the benefit to be allocated to the household) would be calculated as  $0.65c$ . Continuing with the Brazil example, recall that households consuming between 30 and 100 kWh per month receive a 40% discount. Thus, any household reporting spending  $c$  greater than  $(1 - 0.65) * 30p$  per month but less than  $(1 - .40) * 100p$  per month would be assumed to have received the 40% subsidy, and the direct effect would be calculated as  $0.40c$ .<sup>21</sup> Following this method, the amount of benefits we allocated for household energy subsidies was 77% of the amount spent according to national accounts; the discrepancy might be accounted for by leakages—our simulation assumed perfect coverage and no leakages.

<sup>20</sup> This is a simplification of the actual system for illustrative purposes. See Higgins and Pereira (2013) for more details.

<sup>21</sup> Note that there are tranches of spending amounts that do not coincide with the IBT schedule: for example, if the household reports spending  $c$  such that  $(1 - 0.65) * 30p < c < (1 - 0.4) * 30p$ , their total spending  $c$  is not possible given the discontinuous IBT schedule. The value they reported for  $c$  could be due to misreporting, or for example that the survey's reference period does not coincide with the billable month. We have arbitrarily chosen to place individuals in this category with the group who received the 40% subsidy; they could also have arbitrarily been placed in the group who received the 65% subsidy.

Note that a tool for simulating subsidies—which include household energy subsidies with an inverted block tariff structure—is described in Araar and Verme (2012).

#### *Agricultural subsidies*

The incidence of benefits of agricultural subsidies will depend on the elasticity of demand for the agricultural products. If demand is perfectly elastic, the benefit will accrue entirely to the producer, in which case benefits would be imputed based on survey questions revealing who produces the subsidized goods. If it is inelastic, it will accrue entirely to the consumer, in which case the benefits can be estimated using an input-output table as they would be for other subsidized goods, using the method described above. The method to impute agricultural subsidies will depend on the nature of these subsidies and the demand for the products whose inputs are subsidized.

### **x. Constructing Final Income**

#### *Add In-kind Transfers*

The value of in-kind transfers is based on the use of public services as reported in the survey. Details, by category of in-kind transfer, are given below.

#### *Education*

From national accounts, obtain public spending per student by level (pre-school, primary [lower and upper if applicable], secondary [lower and upper if applicable], tertiary [university and technical if applicable]). The spending amount should include administrative costs and *both* recurring and investment spending. Provide the definition of each level (i.e., the corresponding grade levels and age groups). For students who report attending public school, depending on the level they report attending, use the average public spending per student for that level as the valuation of their in-kind benefit from public education, which is added into income when moving from post-fiscal to final income, or from disposable to final income\*. In addition to having a variable for in-kind education benefits, the researcher should create separate variables for benefits at each level (i.e., a variable for pre-school education benefits, another for primary education benefits, etc.) for the more disaggregated analysis that is required on some sheets of the Master Workbook Template.

This method for imputing education transfers will overestimate their redistributive effect, as the monetary value of the transfers received by households is obtained from the budgetary cost of providing these transfers as reported in national accounts, while the totals of other taxes and transfers are not “forced” to be equal to the values in national accounts (and tend

to be smaller according to the survey). To correct, for this, we *scale down* these benefits as follows.<sup>22</sup>

First, obtain a national accounts estimate of disposable income (or total consumption if the analysis uses consumption rather than income data). Take the ratio of total education spending in national accounts to disposable income in national accounts, and then scale down the education benefits in the survey so that the ratio of education benefits in the survey to disposable income in the survey equals the former ratio.

If the main survey being used does not have data on whether school attendance was at public or private institutions, the researcher should search for an alternate survey with data on income and on whether school attendance was public or private. For example, the survey used for our incidence study in the United States (Higgins, Lustig, Ruble, and Smeeding, 2013)—the 2011 Current Population Survey (CPS)—did not include a question about whether school attendance was public or private. We estimated the probability of attending public school for each student attending school in the CPS by using another survey, the 2011 American Community Survey (ACS), which contains variables on public and private school enrollment and income. We performed a probit regression on the population of students attending school, with a dummy variable for attending a public school as the dependent variable and per capita income, race, state, age, and highest level of education in the household as independent variables. The coefficients from this regression were then applied to the same variables in the CPS data to estimate the probability of attending public school for each student attending school. The (scaled down) average amount of education spending per pupil by state was then multiplied by the predicted probability of attending public school to get the expected in-kind education transfer for each student attending school.

Note that in the CPS we don't know which students attended public school so we are not imputing the full (scaled down) value of per pupil spending to anyone; by multiplying each student's predicted probability of attending public school by per pupil spending, we are assigning each student the *expected value* of their in-kind education benefit. As a check of our

---

<sup>22</sup> In previous iterations of CEQ (in particular, in the working papers for Latin American countries published before August 2013 and the special issue of *Public Finance Review*), rather than *scaling down* in-kind benefits to avoid overestimating their redistributive impact, we *scaled up* all other income components item by item for calculations of inequality and redistribution (but not poverty). In other words, each component had its own scaling up factor based on total income from that component in the survey compared to total income from that component according to national accounts. However, in consultation with numerous experts of incidence analysis, we have switched to scaling down the in-kind benefits because of its numerous advantages. First, it requires less information from national accounts; in some countries all of the information necessary to scale up item by item is not available. Second, in many countries, national accounts totals for particular income components are measured with a great deal of noise, so scaling up each income component by its own factor introduces noise into our calculations. Third, scaling down in-kind benefits avoids any confusion that arose under the previous methodology of which calculations required the use of scaled up income and which required the use of non-scaled income.

method, we verify that the average predicted probability from applying the coefficients of the ACS survey to the CPS data is almost identical to the proportion of students attending public school (according to both ACS and administrative data). We also verify that total (scaled down) in-kind education benefits using this method is approximately equal to total (scaled down) education spending in national accounts.

### *Health*<sup>23</sup>

To impute the value received from public health services, the household survey must have information about the use of health services, and distinguish between public care (which is usually services received from the public health system or paid for by public health insurance schemes) and private care. In the absence of information about whether the care received was subsidized by government health spending, a survey question about whether the patient is covered by private insurance can be used as a proxy; i.e., patients who received health care and report having private health insurance are considered to have received private care, and thus received no in-kind transfer, and patients who report *not* having private health insurance are considered to have received public care. Ideally, the survey will also contain one or more questions about the type of service received.

If this information is not available in the survey being used, another survey that has information on both income and utilization of public health services – such as a health survey – should be used. In this case, to calculate final income one must then treat the results from the alternate survey similarly to a secondary source and impute values by quantiles (e.g., ventiles [groups of 5% of the population]) back into the original micro-data. However, for the concentration coefficient of health spending (Sheet D8 of the Master Workbook Template) or its coverage and leakages (Sheet D8 of the Master Workbook Template), one should calculate these directly in the alternate micro-data, without imputing these results back into the original data set.

In addition to data on the use of public health services and the type of services received, data on total government spending on each of the different types of health services in the household survey is required. Some level of disaggregation by type of service received (at a minimum, distinguishing between in-patient and out-patient care) is required, in order to account for the fact that the value of a medical check-up is different from the value of a hospitalization. This data should also be disaggregated by region or state when possible to account for differences in the quality of health services across regions. Data that is disaggregated as described above is generally not available in the main source of public accounts (e.g., from the treasury or ministry of development), but can be obtained instead from national health accounts (e.g., from the health ministry). The spending totals should include administrative costs and *both* recurring and investment spending.

---

<sup>23</sup> This section is largely based on O'Donnell et al. (2008), Chapter 14.

In the event that the care received is partially but not fully subsidized, the amount paid for care by the individual or by private health care providers should be subtracted from the total benefit received by that individual. If public health care in the country being studied is, in general, not fully subsidized (for example, there is not a universal free health care system) but the household survey does not ask how much each individual paid for the service they received or how much was not covered by the public health insurance scheme, each individual's payment can be calculated as the average payment for that service; i.e., it is calculated as the total payment from individuals and private health insurers to the state for that service (available in national health accounts) divided by the total number of individuals receiving that service according to the household survey.

The total annualized health benefits received by an individual are thus defined as

$$h_i = \sum_k \alpha_k \left[ q_{ki} \left( \frac{S_{kj}}{\sum_{i \in j} \omega_i \alpha_k q_{ki}} \right) - f_{ki} \right]$$

where  $q_{ki}$  indicates the number of times that individual  $i$  received care type  $k$  during the recall period,  $S_{kj}$  is the total spending (according to national health accounts) on service  $k$  in the region  $j$  where  $i$  resides,  $i \in j$  indicates that we are summing over all individuals in region  $j$ ,  $\omega_i$  is the expansion factor corresponding to observation  $i$ , and  $\alpha_k$  is the “annualization factor”: for services that have a recall period of one year on the questionnaire (e.g., “How many times in the last year did you receive service  $k$ ?”),  $\alpha_k = 1$ ; for services that have a recall period of four weeks,  $\alpha_k = 13$ , etc.

Finally,  $f_{ki}$  is the user fee paid by individual  $i$  for service  $k$ . In the case of a health system with no user fees, we normally use  $f_{ki} = 0$  (regardless of whether the system is fully or partially subsidized, because the level of subsidization would already be captured by the term  $S_{kj}/\sum_{i \in j} \omega_i \alpha_k q_{ki}$ ) unless other costs such as waiting times are being incorporated in the analysis. When user fees exist, if the survey asks individuals how much they paid for that particular service or has information (sometimes found along with other consumption questions) about how much they paid in health costs,  $f_{ki}$  can be determined from the survey. Note that  $f_{ki}$  could still equal zero for some  $i$ , for example for poor individuals if there are fee exemptions for the poor. In the absence of such survey information, one can determine the average health user fee per visit,  $\bar{f}$ , as  $\bar{f} = \frac{N_k}{\sum_k \sum_i \omega_i \alpha_k q_{ki}}$ , where  $N_k$  is total user fee revenue, reported in public accounts or national health accounts. In other words,  $\bar{f}$  is total user fee revenue divided by the total number of times all individuals in the country utilized any type of public health service. To complete the calculation of total annualized health benefits received by an individual, one would then replace  $f_{ki}$  in the above equation with  $\bar{f}$ .

This method for imputing health transfers will overestimate their redistributive effect, as the monetary value of the transfers received by households is obtained from the budgetary cost of providing these transfers as reported in national accounts, while the totals of other taxes and transfers are not “forced” to be equal to the values in national accounts (and tend to be smaller according to the survey). To correct, for this, we *scale down* these benefits as follows.

First, obtain a national accounts estimate of disposable income (or total consumption if the analysis uses consumption rather than income data). Take the ratio of total health spending in national accounts to disposable income in national accounts, and then scale down the health benefits in the survey so that the ratio of education benefits in the survey to disposable income in the survey equals the former ratio.

In countries with a contributory public health insurance scheme, we are also interested in knowing the concentration of coverage, so the concentration coefficients and coverage and leakages sheets of the Master Workbook Template (Sheets D8 and D9, respectively) include a row for Contributory Public Health Insurance in addition to the row for Health Spending. The latter is based on use, using the total annualized health benefits,  $h_i$ , calculated as explained above. The former is calculated using a variable equal to zero for individuals not covered by the contributory public health insurance schemes and equal to the value of a basic health package for covered individuals.

### *Housing*

Impute the in-kind value received by those who live in publicly (fully or partially) subsidized housing. Ideally, the survey will include information on who lives in subsidized housing and, if it is only partially subsidized, how much they paid in rent. The market value of their subsidized housing can be determined using a regression methodology (similar to the regression methodology described to impute the value of owner-occupied housing under the section *Imputed Rent for Owner Occupied Housing*). If housing is only partially subsidized, the amount they pay in rent should be subtracted from this total. For the observations for which this method results in a negative value, it should be replaced by zero; however, if a negative value results for many observations, this could be an indication that the linear model used to predict housing values is not a good fit and should be revisited.

### *Infrastructure and Other Public Goods*

We do not attempt to impute values for infrastructure and other public goods. O’Dea and Preston (2012) lay the groundwork for estimating the distributional impact of public goods, but their methods have yet to be implemented empirically as far as we know.

Nevertheless, we can estimate equity in *access* to infrastructure (such as electricity, running water, roads). Which components of infrastructure are included here depends on the questions in the survey. After creating a dummy variable that equals 1 for individuals with

access and 0 for individuals without access, the concentration coefficient of access can be estimated and a row for that component of infrastructure can be added to Sheet D9.

## **xii. Complementary Analysis: Tax Expenditure and Subsidized Portion of Social Security**

### *Tax Expenditures*

Tax expenditures result in people paying less indirect taxes, so they should not be added to income (because that would be double-counting). Nevertheless, many of the output tables include tax expenditures; for example, in the incidence table there is a column to the right where the incidence of tax expenditures should be estimated, while the concentration coefficients table has a row for the concentration coefficient and budget size (i.e., forgone revenue) of tax expenditures.

### *Subsidized Portion of Social Security*

Although contributory pensions are not split up into a subsidized and non-subsidized portion in the main analysis (they are considered part of market income, in their entirety, in the benchmark case, and as a government transfer, in their entirety, in the sensitivity analysis), we do separate them into a subsidized and non-subsidized component for a complementary analysis. We propose two methods to impute how the subsidized portion of social security is distributed among households (calculations should be provided using both methods): a) divide the total social security deficit, defined as total social security payments minus total contributions to the social security system, by the number of people who receive pensions and assign the per capita value to each individual who received a pension; b) assign the subsidy in proportion to the pensions each household receives (i.e., the subsidized portion of pensions are distributed identically to total pensions; if forty percent of the social security system is subsidized, then for each individual who received a contributory pension, it is assumed that forty percent of that pension is subsidized). These two methods will give a lower and upper bound for the incidence of the subsidized portion of pensions.

## **3. Incidence Results and Indicators**

This section describes the informational requirements and indicators as well as the presentational format of CEQ in the Master Workbook Template. In addition to the information contained in this document and in the Master Workbook Template itself, authors can use the sample Stata code included below under each corresponding item as a guideline.<sup>24</sup>

---

<sup>24</sup> In the future, we hope to develop computational software and tools (in the form of Stata programs) to systemize the process of producing CEQ outputs once the country authors have prepared the data following the second section of the handbook. The computational software would facilitate the process of carrying out a consistent and comparable analysis using our methodological framework and would generate publication-ready tables and graphs. The software would also facilitate sensitivity analyses and robustness checks which would test the sensitivity of the results to alternative taxonomical, imputational, and behavioral assumptions.



The Master Workbook Template contains four main sections, each with various subsections (sheets). The first section is background information. This section both asks for background information about the country (such as the evolution of inequality and poverty over time and public accounts information) as well as descriptions of the various components of social spending, such as the tax system, flagship cash transfer programs, the health system, etc., in the country being analyzed. The second section asks for survey information, such as the exact survey questions used to construct each component of the income concepts. The third section, methodological aspects and assumptions, both defines many of CEQ's methodological assumptions (described in more detail in this document) and asks country authors to describe the specifics of applying that methodology to their country, or of additional assumptions they made. The fourth section contains the results and indicators of the incidence analysis. Here, we focus on the incidence results and indicators section. We begin by overviewing some additional definitions that are necessary to complete this section of the Template. We then go sheet-by-sheet through this section, describing the contents of each sheet and any additional definitions needed to complete the sheet. When appropriate, we include sample Stata code to produce the data that will be put in the sheet's tables.

### *General Definitions*

Here we define some general concepts that are used throughout the Template.

#### *Progressivity*

Since one of the criteria for evaluating the distributive impact of fiscal policy depends on the extent of progressivity of taxes and transfers, this is a good place to review the definitions used in the literature of what constitutes progressive taxes and transfers. To determine if a tax or transfer is progressive, concentration curves, concentration coefficients, and the Kakwani (1977) index are commonly used.

Concentration curves are constructed similarly to Lorenz curves but the difference is that the vertical axis measures the proportion of the tax (transfer) under analysis paid (received) by each quantile. Therefore, concentration curves (for a transfer targeted to the poor, for example) can be above the diagonal (something that, by definition, could never happen with a Lorenz curve). Concentration coefficients are calculated in the same manner as is the Gini; for cases in which the concentration coefficient is above the diagonal, the difference between the triangle of perfect equality and the area under the curve is negative, which cannot occur with the Gini for the income distribution by definition. The data used to generate concentration curves and coefficients are derived from incidence analyses. The technical definitions of the Lorenz curve and concentration curve are given in section 4.xiv.

The terms “progressive” and “regressive” are used in two different senses in the literature on taxes and transfers (Lustig, Pessino, and Scott, 2013). We borrow their concise summary here:

The progressivity/regressivity of a transfer can be measured in absolute terms, by comparing taxes/transfers between quantiles, or in relative terms, by comparing taxes/transfers as a percentage of the (pre-tax/transfer) income of each quantile. In the tax incidence literature, where the fiscal application of the term “progressive/regressive” originated, it is used exclusively in the relative sense, while in the benefit (and tax-benefit) incidence literature it is common practice to use the absolute as

well as the relative concepts, distinguishing these two terms explicitly (e.g. Lindert, Skoufias, and Shapiro, 2006; Scott, 2011) or equivalent ones: “weakly/strongly progressive,” “pro-poor/pro-rich” (e.g. O’Donnell et al., 2008; Wagstaff, 2012). The reason for the latter practice is that the issue of practical interest in the case of transfers is not regressivity in relative terms, which is rarely observed for transfers (making the description of a transfer as progressive in relative terms barely informative in benefits incidence analysis contexts), but the concentration of benefits on higher or lower income groups, or their redistributive efficiency. (Lustig, Pessino, and Scott, 2013)

Since CEQ assesses the progressivity of both taxes and transfers, we have opted for the relative definition. Hence, a transfer is progressive when the proportion received (as a percentage of market income) decreases with income. This is consistent with an intuitively appealing principle: a transfer or tax is defined as progressive (regressive) if it results in a less (more) unequal distribution than that of market income. We distinguish between transfers that are progressive in absolute terms and progressive in relative terms. In particular:

1. A tax is everywhere progressive (regressive) if the proportion paid – in relation to market income – increases (decreases) as income rises.<sup>25</sup> In practice, taxes are not *everywhere* progressive; for example, if one household manages to evade the tax while another household with slightly lower income and another with slightly higher income do not, it will violate the definition of being *everywhere progressive*. We consider a tax progressive (regressive) if its concentration curve lies everywhere below (above) the market income Lorenz curve. A necessary but not sufficient condition for this is that the concentration coefficient is positive and larger (smaller) than the market income Gini. This necessary but not sufficient condition is equivalent to saying that the Kakwani index, defined for taxes as the tax concentration coefficient minus the market income Gini, will be positive (negative) if a tax is everywhere progressive (regressive).

Note that the concentration curve of the tax may *cross* the market income Lorenz curve, in which case it is ambiguous (i.e., neither progressive nor regressive). Its concentration coefficient may be either less than or greater than the market income Gini. Hence, we use concentration curves—and not concentration coefficients or Kakwani indices alone—to determine progressivity.

2. A transfer is everywhere progressive if the proportion received—in relation to market income—decreases as income rises. There are two types of progressive transfers: absolute and relative. A transfer will be progressive in absolute terms if the per capita amount received increases as income rises. A transfer will be progressive in relative terms if the proportion received in relation to market income decreases as income rises but not so the per capita transfer. Again, transfers in practice are usually not *everywhere progressive* because someone might not receive the transfer while a slightly poorer and a slightly richer person both do. We define a transfer as *progressive in absolute terms* if its concentration curve will lie everywhere above the 45-degree line. A necessary but not sufficient condition for this is that the concentration coefficient is negative, or equivalently that the Kakwani index, defined for transfers as the market income Gini minus the transfer’s concentration coefficient, is positive and higher than the market income Gini.<sup>26</sup> We define a transfer as *progressive in relative*

<sup>25</sup> For more on the concept of a tax being everywhere progressive, see Duclos (2008).

<sup>26</sup> The index originally proposed by Kakwani (1977) only measures the progressivity of taxes. It is defined as the tax’s concentration coefficient minus the market income Gini. To adapt to the measurement of transfers, Lambert (1985)

*terms* if its concentration curve lies everywhere between the market income Lorenz curve and the 45-degree line. A necessary but not sufficient condition for this is that the concentration coefficient is positive and lower than the market income Gini, or equivalently that the Kakwani index is positive if a transfer is progressive in relative terms.

If the concentration curve of a transfer crosses the 45 degree line (this could be from above or below and any number of times) but still lies everywhere above the market income Lorenz curve, it is unambiguously progressive, but we cannot say unambiguously whether it is progressive in absolute terms, even if its concentration coefficient is negative.

3. A transfer is everywhere regressive if the proportion received—in relation to market income—increases as income rises. Again, in practice transfers will not be *everywhere* regressive. We define a transfer as unambiguously *regressive* if the concentration curve lies everywhere below the market income Lorenz curve. A necessary but not sufficient condition for this is that the concentration coefficient is positive and greater than the market income Gini, or equivalently, that the Kakwani index is negative.

If the concentration curve of a transfer crosses the market income Lorenz curve, we cannot unambiguously say that the transfer is progressive or regressive. Its concentration coefficient may be either less than or greater than the market income Gini. Hence, we use concentration curves—and not concentration coefficients or Kakwani indices alone—to determine progressivity.

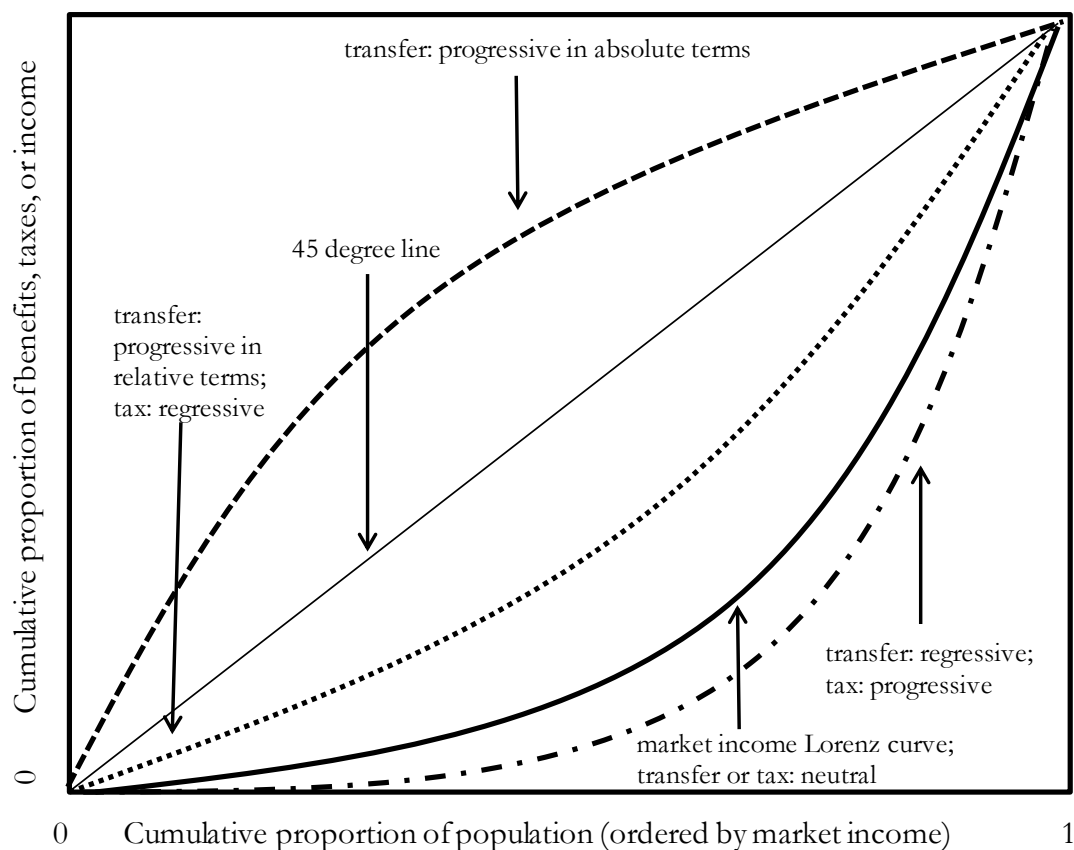
4. A tax or transfer will be neutral (in relative terms) if the distribution of the tax or the transfer coincides with the distribution of market income. A necessary but not sufficient condition for this is that the concentration coefficient is equal to the market income Gini. Equivalently, the Kakwani index will equal zero if a tax or transfer is neutral.

The four cases are illustrated graphically in Diagram 2.

## **Diagram 2. Concentration Curves for Progressive and Regressive Transfers and Taxes**

---

suggests that in the case of transfers it should be defined as market income Gini minus the concentration coefficient (i.e., the negative of the definition for taxes) to make the index positive whenever the change is progressive.



### *Total CEQ Social Spending*

In both the benchmark case and the sensitivity analyses, Total CEQ Social Spending includes government spending at all levels on health, education, and social assistance. In the benchmark case it does not include spending on social security pensions, but does include spending on programs such as unemployment benefits which may be part of the contributory system but are intended to smooth idiosyncratic shocks. In the Sensitivity Analysis 1 (the case where contributory pensions are considered a transfer), we define Total CEQ Social Spending plus Contributory Pensions. These numbers are presented both in absolute terms in local currency and as a percentage of GDP. The values for each component should be taken from public sector accounts for the same year as the year of the household survey being used. A breakdown of Total CEQ Social Spending, which shows the value of each of its components, must be provided on the “Macroeconomic and Public Accounts” sheet in the Background Information section of the Template (see Table 1 below for an example from Brazil).

### *CEQ Social Spending in Incidence Analysis*

This number, which is by definition less than (or potentially equal to) Total CEQ Social Spending, only includes the components of Total CEQ Social Spending that are included in

the analysis. In other words, if a particular component of social assistance is not captured by the survey and cannot be imputed, simulated, or otherwise incorporated into the analysis, then spending on that component is *not* included in CEQ Social Spending in Incidence Analysis. Table 1 below presents an example for Brazil, in which the rows highlighted in gray are not included in the analysis and thus spending on those items is not part of CEQ Social Spending in Incidence Analysis. For the case where pensions are considered a transfer (i.e., Sensitivity Analysis 1) we also define CEQ Social Spending plus Contributory Pensions Incidence Analysis.

**Table 1. Breakdown of CEQ Social Spending in Brazil, 2009**

Spending Component	Included in Analysis	Billions of reais	% of GDP	Notes and Source
<i>Direct Cash and Food Transfers</i>				
Bolsa Família (CCT)	Yes	12.5	0.4	a
BPC (Non-contributory pensions)	Yes	16.9	0.5	a
Child Labor Eradication	Yes	0.3	0.0	b
Bolsa Escola, Auxílio Gás, and other auxílios	Yes	0.4	0.0	b
Other elements of Basic Social Protection	No	2.4	0.1	b, c
Minimum Income Programs	Yes	0.1	0.0	d
Assistance from PIS/PASEP	Yes	7.3	0.2	e
Unemployment benefits	Yes	18.6	0.6	e
Professional qualification grant	No	0.1	0.0	e
Food for workers program	No	0.5	0.0	e
Scholarships	Yes	3.5	0.1	f
Basic food basket	Yes	0.0	0.0	g
Other food access programs	No	0.6	0.0	c, g
Special circumstances pensions	Yes	72.6	2.3	h
<i>Social Assistance (not direct transfers)</i>				
Assistance to the elderly and disabled	No	19.0	0.6	i
Assistance to children and adolescents	No	2.7	0.1	i
Community assistance	No	18.1	0.6	i
Other	No	4.3	0.1	i
<i>Education</i>				
Early childhood education	Yes	9.6	0.3	i
Primary education	Yes	75.1	2.4	i
Secondary education	Yes	12.0	0.4	i
Tertiary education	Yes	26.0	0.8	i
Other	Yes	46.5	1.5	i
<i>Health</i>				
Primary care	Yes	33.6	1.1	i
In-patient care	Yes	81.7	2.6	i
Preventative care	Yes	9.1	0.3	i
Other	Yes	41.6	1.3	i
<b>Social Spending Analyzed (Benchmark)</b>	<b>Yes</b>	<b>467.4</b>	<b>14.7</b>	
<b>Total Social Spending (Benchmark)</b>	<b>Part</b>	<b>515.1</b>	<b>16.2</b>	
<i>Contributory Pensions</i>				

Contributory pensions (INSS)	Yes	164.8	5.2	j
Other federal contributory pensions	Yes	53.7	1.7	c, i
State contributory pensions	Yes	56.1	1.8	i
Municipal contributory pensions	Yes	14.0	0.4	i
<b>Social Spending Analyzed (Sensitivity Analys.)</b>	<b>Yes</b>	<b>756.0</b>	<b>23.7</b>	
<b>Total Social Spending (Sensitivity Analysis)</b>	<b>Part</b>	<b>803.7</b>	<b>25.2</b>	k

Notes and data sources: All spending totals include spending at the federal, state, and municipal levels, unless otherwise specified. (a) Amount paid in transfers. SAGI and MDS (2012). (b) MDS (2011). (c) Calculated as a residual by the authors. (d) This is the total for Renda Cidadã in São Paulo state, which is the largest minimum income program. Secretaria do Desenvolvimento Social, Governo do Estado de São Paulo. (e) Ministério do Trabalho (2011). (f) Portal da Transparência, Controladora Geral da União. (g) Ministério da Agricultura, Pecuária e Abastecimento (2009). (h) This is the total for pensões and outros benefícios from Ministério de Previdência e Assistência Social (2009). (i) Ministério da Fazenda (2010). (j) This is the total for aposentadorias and benefício mensal. Ministério de Previdência e Assistência Social (2009). (k) This number can be compared with Brazil's total social spending as a percent of GDP according to the UN Economic Commission for Latin America and the Caribbean of 27 percent.

Source: Higgins and Pereira (2013).

### *Deciles*

Each decile represents ten percent of the population. Individuals are ordered by income from poorest to richest, with the “first decile” referring to the poorest decile, and the “tenth decile” referring to the richest. Note that the division should be done such that the expanded population in each decile is equal (or approximately equal), rather than the number of raw observations in each decile. The expanded population refers to the number of individuals when the appropriate expansion factors are applied to each observation.<sup>27</sup> Individuals in the same household should be kept in the same decile, whereas individuals in different households with the same income may be arbitrarily allocated to different deciles if they are near the cut-off, in order to keep decile sizes approximately equal. This is not possible with Stata's built-in command `xtile`, and is best accomplished with the user-written command `quantiles` (written by Rafael Guerreiro Osorio; to install, type `ssc install quantiles` in the command box of Stata). Let household per capita market income be saved as `ym`, the variable containing the identifying code for each household be called `hh_code`, and the variable containing the expansion factor be called `s_weight`. Then, the following command will create market income deciles following the instructions above, and create a new categorical variable called `ym_decile` containing the decile of each observation (i.e., the new variable will be an integer ranging from 1 to 10):

```
quantiles ym [iweight=s_weight], gen(ym_decile) n(10) k(hh_code)
```

<sup>27</sup> Expansion factors are a type of sampling weight. Sampling weights re-weight the sample to account for the non-random stratified sample design. Expansion factors are sampling weights that are scaled such that they sum to the total population of the country (if the survey is representative at the national level).

Some output tables are non-anonymous, in other words, they follow identified individuals, so for example the first decile always refers to the poorest ten percent of the population by initial income (i.e., market or net market income, as specified). For example, in the incidence table we are looking at the change in incomes caused by various taxes and transfers to the incomes of identified individuals: we want to know by how much the incomes of those who are initially in the poorest ten percent, etc. changed. On the other hand, other tables are anonymous so we allow re-ranking between income concepts. For example, in the income distributions table we are comparing the market incomes of the poorest ten percent of the population ranked by market income to the disposable incomes of the poorest ten percent of the population ranked by disposable income, even though these may not be the same individuals.

Since deciles must be created for each income definition, as well as for the benchmark case and each sensitivity analysis, it is wise to use loops in combination with the `quantiles` command. If `ym_BC` represents benchmark case market income, `ym_SA1` represents Sensitivity Analysis 1 market income, etc., the code would look like:

```
foreach x in BC SA1 SA2 {
  foreach i in m n d pf fstar f {
    quantiles y`i'_'`x' [iw=s_weight], gen(y`i'_'`x'_decile) n(10) k(hh_code)
  }
}
```

In the code for non-anonymous sheets such as the incidence analysis sheet, only the decile variables `ym*_decile` would be used (where `*` is a wildcard marker; `ym*_decile` indicates all variables in the data set beginning with `ym_` and ending with `_decile`) – in other words, only the market income deciles are used (or net market where specified). On the other hand, in the anonymous sheets such as the income distributions sheet, all the variables `y*_decile` would be used – in other words, income deciles change with each income concept.

### *Poverty Lines*

All poverty lines are absolute and income- or consumption-based. We use the following poverty lines: the standard international poverty lines of \$1.25 PPP per person per day (which we call "ultra-poverty"), \$2.50 PPP per person per day (extreme poverty), \$4 PPP per person per day (moderate poverty), the official poverty line, which preferably distinguishes between urban and rural areas and possibly by regions, and poverty lines calculated by an international organization for the country. (For countries in Latin America, the latter are from the UN Economic Commission for Latin American and the Caribbean [ECLAC, 2010, Table A5].)

To convert the international poverty lines in purchasing-power parity (PPP) adjusted US dollars into local currency poverty lines, the PPP conversion rate should be selected for the

same year as the survey. The PPP conversion rate should be based on private consumption rather than GDP; if obtained from the World Development Indicators Databank (<http://databank.worldbank.org>), the series “PPP conversion factor, private consumption (LCU per international \$)” should be used. The yearly international poverty line in local currency is equal to the PPP per day poverty line times the PPP conversion factor (of local currency units per PPP dollar), times 365 days per year. For example, in the case of Brazil, the private consumption-based PPP conversion factor for 2009 (the same year as the household survey being used for Brazil) is 1.71 Brazilian reais = \$1 PPP, so the \$4 PPP per day international poverty line would be converted into local currency (reais) per year as follows:

$$\frac{\$4 \text{ PPP}}{1 \text{ day}} \times \frac{1.71 \text{ reais}}{\$1 \text{ PPP}} \times \frac{365 \text{ days}}{1 \text{ year}} = \frac{2502 \text{ reais}}{1 \text{ year}}$$

Thus, the \$4 PPP per day international poverty line is equivalent to 2,502 reais per year. Note that to convert a monthly national poverty lines in local currency to \$PPP per day you need to divide the line by the PPP conversion factor, multiply by 12 and divide by 365.

Note that if the survey is taken over many months, the data should first be deflated to a specific month. This is often facilitated by temporal deflating factors included as one of the data set’s variables.

### *Income Groups*

We define a set of income groups, beginning with the three poor groups defined above: the ultra-poor (household per capita income less than \$1.25 PPP per day), the extreme poor (household per capita income greater than or equal to \$1.25 PPP per day and less than \$2.50 PPP per day), the moderate poor (household per capita income greater than or equal to \$2.50 PPP per day but less than \$4 PPP per day). The non-poor income groups are the vulnerable (household per capita income greater than or equal to \$4 PPP per day and less than \$10 PPP per day), the middle class (household per capita income greater than or equal to \$10 PPP per day but less \$50 PPP per day), and the rich (household per capita income greater than \$50 PPP per day). These income groups were formulated with middle income countries, particularly those in Latin America, in mind.

The \$1.25 PPP per day line approximately represents the average national poverty line of the bottom fifteen low-income, less-developed countries (Chen and Ravallion, 2010); thus in the context of middle-income countries we call those living on less than \$1.25 PPP per day the “ultra-poor”. The \$2.50 and \$4 PPP per day poverty lines are commonly used as extreme and moderate poverty lines for Latin America, and roughly correspond to the median official extreme and moderate poverty lines in those countries (CEDLAS and World Bank, 2012). The \$10 PPP per day line is the upper bound of those vulnerable to falling into poverty (and thus the lower bound of the middle class) in three Latin American countries, calculated by Lopez-Calva and Ortiz-Juarez (2013). Ferreira et al. (2013) find that an income of around \$10 PPP also represents the income at which individuals in various Latin American countries tend to self-identify as belonging to the middle class and use this as further justification that it should be used as the lower bound of the middle class. The \$10 PPP per day line was also used as the lower bound of the middle class in Latin America in Birdsall (2010) and in



developing countries in all regions of the world in Kharas (2010). The \$50 PPP per day line is the upper bound of the middle class proposed by Ferreira et al. (2013).

The following Stata code provides an example for converting this set of international lines in \$ PPP per day into local currency per year, saving these lines as local macros, and creating income groups by comparing market income to these lines. The example once again comes from Brazil, where the 2009 consumption-based PPP conversion factor was 1.71 Brazilian reais = \$1 PPP (in practice, more decimal places should be used for increased accuracy, as below).

A loop is used to loop over the benchmark case and sensitivity analyses. The /// at the end of some lines tells Stata that the next line is a continuation of the code from the previous line; note that /// can only be used in do files, and not in the command prompt.

```
local PPP=1.7116 // PPP conversion factor for Brazil 2009 (consumption-based)
                  // from databank.worldbank.org
local PPPyr=`PPP'*365 // Brazil data is annual; if monthly also divide by 12
local lines 125 250 400 1000 5000 // $1.25 etc. but won't work with decimals
foreach n in `lines' {
    local PL`n'=(`n'/100)*`PPPyr'
}
label define groups 1 "y<1.25" 2 "1.25<y<2.5" 3 "2.5<y<4" 4 "4<y<10" ///
                    5 "10<y<50" 6 "y>50"
foreach x in BC SA1 SA2 {
    generate ym_`x'_group=.
    replace ym_`x'_group=1 if ym_`x'<`PL125'
    replace ym_`x'_group=2 if ym_`x'>=`PL125' & ym_`x'<`PL250'
    replace ym_`x'_group=3 if ym_`x'>=`PL250' & ym_`x'<`PL400'
    replace ym_`x'_group=4 if ym_`x'>=`PL400' & ym_`x'<`PL1000'
    replace ym_`x'_group=5 if ym_`x'>=`PL1000' & ym_`x'<`PL5000'
    replace ym_`x'_group=6 if ym_`x'>=`PL5000'
    label values ym_`x'_group groups
}
```

### *Sampling Weights and Stratification*

Since most surveys are not simple random samples, calculations must always include sampling weights (specifically, expansion factors). If our expansion factors is called `s_weight`, we implement this by adding `[pw=s_weight]` to our command. Some commands in Stata do not work with “pweights” (sampling weights) so one must instead use “iweights” (importance weights) or “aweight” (analytic weights). In the sample Stata code included in this handbook we always specify which weight is possible with the command being used.

When standard errors are being calculated, the complex stratified sample design must be taken into account. For standard error estimations, using the sampling weights is *not sufficient*. If the survey you are using has a three-stage sample design, it will have, in addition to the commonly used variable for each observation's sampling weight, a variable for the primary sampling unit and the strata. For a survey with a two stage sample design, it will have a variable for the sampling weight and primary sampling unit only (which is sometimes confusingly called strata in the data sets). In Stata, the survey sample design variables (sampling weight, strata, and primary sampling unit) can be saved with the data set using the `svyset` command (followed by the `save` command so that the next time the data set is opened, Stata will remember the survey sampling design). Once the survey sample design is saved in the data set, commands that are designed to produce standard errors that account for stratification and clustering can be told to account for them using the `svy:` prefix. In addition, some user-written commands such as those that are part of the DASP package (Duclos and Araar, 2012)—e.g., `digini`, `dientropy`, `dinineq`, and `difgt` used for Sheet D1—automatically use the information about sampling weights, strata, and primary sampling units. However, for programs not in the DASP package, the user should never assume that the command automatically incorporates the survey sampling design information.

Let the sampling weight variable in our data set be saved as `s_weight`, the strata be saved as `s_strata`, and the primary sampling unit be saved as `s_unit`. Then the syntax for saving the sampling information would be

```
svyset s_unit [pw=s_weight], strata(s_strata)
```

In the case of a survey with a two-stage sample design rather than three-stage, the `strata()` option would not be included. After saving, closing, and re-opening the data set, one can make sure that the survey sampling design is saved in the data set by typing `svydes`.

Having outlined some relevant definitions, we now turn to each sheet of the Master Workbook Template's incidence results and indicators tables (i.e., the fourth section of the Template) individually.

#### **i. Sheet D1 – Reduction in Inequality and Poverty**

This sheet shows the change in inequality and poverty measures across the different income concepts, as well as the significance of these changes and the CEQ effectiveness indicators. The inequality indicators are the Gini, Theil, and 90/10 indices. The poverty indices included are the

headcount index, poverty gap index, and squared poverty gap index.<sup>28</sup> The CEQ effectiveness indicators will be defined under the section Sheet D2 – Effectiveness Indicators (even though they also appear on Sheet D1), since that output sheet is devoted entirely to effectiveness indicators.

Graphically, the Gini is represented by twice the area between the market income Lorenz curve and the line of equality. The market income Lorenz curve maps the cumulative share of market income on the vertical axis against the cumulative share of the population, ordered by market income, on the horizontal axis. It equals  $2 \int_0^1 (p - L(p)) dp$ , where  $p$  is the cumulative proportion of the total population when individuals are ordered in increasing income values using market income (graphically,  $p$  is also equivalent to the line of perfect equality) and  $L(p)$  is the Lorenz curve. There are various user-written Stata commands to compute the Gini, including `igini` (part of the Distributive Analysis Stata Package [DASP; Araar and Duclos, 2012]), `concindexi` (calculates concentration coefficients and Ginis; written by Amadou Bassirou Diallo), and `ainequal` (written by João Pedro Azevedo).

Sheet D1 also asks for the change in Gini and the statistical significance of that change from zero, measured by the p-value. This encounters computational nuances, since the p-value of the change is a function of the variance of  $G(a) - G(b)$ , where  $G(a)$  is the Gini of income concept  $a$  (in the case of Sheet D1, market or net market income), and  $G(b)$  is the Gini of income concept  $b$ . Thus one must calculate  $\text{Var}[G(a) - G(b)] = \text{Var}(G(a)) + \text{Var}(G(b)) - 2\text{Cov}(G(a), G(b))$ . The nuance lies in the fact that there are multiple ways to calculate  $\text{Cov}(G(a), G(b))$ , as described in Yitzhaki and Schechtman (2013, Chapter 3).

For simplicity and to avoid error, we suggest using the user-written Stata command `digini` (part of the DASP package [Araar and Duclos, 2012]), which automatically calculates the significance of a change in Gini. The drawback of this command is that it is computationally burdensome in terms of the computer resources it requires, so using it can result in a slow do-file.<sup>29</sup> The following sample Stata code uses `digini` to produce a matrix analogous to the Gini portion of the main table in Sheet D1, but without effectiveness indicators. Note that the `digini` command does not allow the incorporation of weights using the traditional `[weight]` syntax, but instead automatically uses the weights that are saved into the dataset using the `svyset` command. The example below also loops through the benchmark case and sensitivity analyses, with income variables saved in Stata using the same names as in previous examples: e.g., `ym_BC` is benchmark case market income.

```
svyset s_unit [pw=s_weight], strata(s_strata) // remember to svyset before
// using commands from DASP package

quietly {
* Preliminaries
```

---

<sup>28</sup> The importance of including distribution-sensitive poverty measures such as the squared poverty gap in incidence analyses—rather than relying only on the more commonly used headcount index—is illustrated empirically in DeFina and Thanawala (2004).

<sup>29</sup> Do-file refers to the text file containing Stata code, which is saved with the `.do` extension.

```

count
local N = r(N) // for degrees of freedom for t-test. weights not used to
                // determine degrees of freedom
local xlist BC SA1 SA2 SA3 // to loop through benchmark and sensitivities
local ylist m n d pf fstar f // income definitions
local i=1
foreach y in `ylist' {
    local `y'=`i'
    local i=`i'+1
} // this loop makes locals m n d pf fstar f that equal 1 2 3 4 5 6 which I
    // use later to put my results in the results matrix (i.e. this loop does
    // the equivalent of a reverse tokenize for `ylist')
* Calculations
foreach x in `xlist' {
    noisily display "`x'"
    digini ym_`x' yn_`x' // requires installation of DASP
    matrix d1 = e(d1) // e(d1), e(d2), and e(di) are matrices saved by -digini-
    matrix d2 = e(d2)
    matrix di = e(di)
    scalar measurem = d1[1,1] // ineq for market income
    scalar measuren = d2[1,1] // ineq for net market income
    scalar diffmn = di[1,1] // difference
    scalar edi12 = di[1,2] // se of diff
    scalar pvaluemn = 2*ttail( `N'-2, abs(diffmn/edi12) ) // pvalue of diff
    matrix results = J(5,6,.z) // blank matrix for results
    matrix results[1,1] = measurem
    matrix results[1,2] = measuren
    matrix results[2,2] = diffmn
    matrix results[3,2] = pvaluemn
    foreach y in d pf fstar f {
        foreach b in m n {
            digini y`b'_`x' y`y'_`x'
            matrix d2 = e(d2)
            matrix di = e(di)
            scalar measure`y' = d2[1,1] // ineq for looped income measure
            scalar diff`b`y' = di[1,1] // diff btwn mkt or net mkt and looped
                // income measure
            scalar edi12 = di[1,2] // se of diff
            scalar pvalue`b`y' = 2*ttail( `N'-2, abs(diff`b`y'/edi12) ) // pvalue
        } // end of b-loop
        matrix results[1,`y'] = measure`y' // note ``y'' uses the locals I
            // created earlier with the reverse tokenize loop
        matrix results[2,`y'] = diffm`y'
        matrix results[3,`y'] = pvaluem`y'
        matrix results[4,`y'] = diffn`y'
        matrix results[5,`y'] = pvaluen`y'
    } // end of y-loop
    matrix colnames results = MARKET NET_MARKET DISPOSABLE POST-FISCAL ///
        FINAL* FINAL
    matrix rownames results = Gini Diff_wrt_Market (p-value) ///
        Diff_wrt_Net_Mkt (p-value)
    noisily matlist results, title("Sheet D1 - Gini") names(all) ///
        aligncolnames(ralign) nodotz underscore format(%11.4f) twidth(16) ///
        lines(columns) linesize(100)
} // end of xlist-loop
} // end quietly

```

The Theil index, also known as the Theil's T index, is a member of the family of generalized entropy inequality measures, with the parameter  $\theta = 1$ . Hence, it is sometimes written as GE(1), and is defined as

$$GE(1) = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{\bar{y}} \ln \left( \frac{y_i}{\bar{y}} \right)$$

where  $y_i$  is individual  $i$ 's (household per capita) income, using whichever income concept the Theil is being calculated for, and  $\bar{y}$  denotes average income. Expansion factors are omitted from the above equation for notational simplicity, but they should of course be included in the calculation. A matrix analogous to the Theil portion of Sheet D1 can be produced using the same syntax as in the above Gini example, except replacing the line `digini ym_`x' yn_`x'` with `dientropy ym_`x' yn_`x', theta(1)` and similarly for the other `digini` line. The `dientropy` command is also a component of the DASP package.

The 90/10 measure how the relatively rich fare compared to the relatively poor. Specifically, after dividing the population into 100 income percentiles, it is calculated as the average income of those in the 90<sup>th</sup> percentile divided by the average income of those in the 10<sup>th</sup> percentile. A matrix analogous to the 90/10 portion of Sheet D1 can be produced using the same syntax as in the above Gini example, except replacing the line `digini ym_`x' yn_`x'` with `dinineq ym_`x' yn_`x', p1(.9) p2(.1)`. The `dinineq` command is also a component of the DASP package.

The poverty indices included in Sheet D1 are members of the FGT class of poverty measures (Foster, Greer, and Thorbecke, 1984). Let households be ranked by  $y_i$ , household per capita income for the income variable for which poverty is being measured, from poorest to richest. Let the poverty line being used be denoted  $z$ . Then, following Foster, Greer, and Thorbecke (1984), denote  $g_i = z - y_i$  the income shortfall of individual  $i$  (i.e., the increase in income that would be required for individual  $i$  to no longer be poor), and let  $q$  denote the number of poor individuals and  $n$  the total number of individuals. Then the FGT class of poverty measures is a function of the population's ordered income vector  $\mathbf{y} = (y_1, \dots, y_n)$  and the poverty line  $z$ , and is defined as follows:

$$P_\alpha(\mathbf{y}; z) = \frac{1}{n} \sum_{i=1}^q \left( \frac{g_i}{z} \right)^\alpha.$$

The headcount index, or the proportion of the population that has income below the poverty line, is equal to the above equation with parameter  $\alpha = 0$ . The poverty gap, which measures the average shortfall (over the whole population, where non-poor individuals are assigned a shortfall of zero) as a proportion of the poverty line, is equal to the above equation with the parameter  $\alpha = 1$ . Finally, the squared poverty gap is distribution-sensitive, giving a higher weight to those who are poorer by weighting each individual's shortfall relative to the poverty line by itself (i.e., squaring it). It is equal to the above equation with parameter  $\alpha = 2$ . Expansion factors are omitted from the above equation for notational simplicity, but should of course be included in the calculation.

There are many user-written Stata programs to calculate the FGT indices, such as `apoverity` (written by João Pedro Azevedo). However, since Sheet D1 also asks for the significance of changes in poverty over different income concepts, we again recommend using the DASP package. The syntax

is somewhat different than before due to the way results are stored for poverty measures as opposed to inequality measures in DASP, as illustrated by the sample code below. The example below produces results for the international poverty lines, which are saved in locals `PL125', `PL250' and `PL400', which can be done using the sample code from the poverty lines section. As usual, it loops over the benchmark case and sensitivity analyses.

```
quietly {
local ylist m n d pf fstar f // income definitions
local i=1
foreach y in `ylist' {
  local `y'=`i'
  local i=`i'+1
  } // this loop makes locals m n d pf fstar f that equal 1 2 3 4 5 6 which I
  // use later to put my results in the results matrix (i.e. this loop does
  // the equivalent of a reverse tokenize for `ylist')
foreach x in BC SA1 SA2 SA3 { // loop over benchmark etc.
  noisily display "Scenario: `x'"
  foreach n in 125 250 400 { // loop over poverty lines
    scalar n_as_decimal = `n'/100
    noisily display "Poverty Line: $" n_as_decimal " PPP"
    foreach alpha in 0 1 2 { // alpha parameters for headcount ratio, poverty
      // gap, squared poverty gap
      difgt ym_`x' yn_`x', alpha(`alpha') pline1(`PL`n'') pline2(`PL`n'')
      scalar measurem = r(est1) // pov for market income
      scalar measuren = r(est2) // pov for net market income
      scalar diffmn = r(est3) // difference
      scalar pvaluemn = 2*ttail(`N'-2, abs(r(est3)/r(std3))) // pvalue of dif
      matrix results = J(5,4,.z)
      matrix results[1,1] = measurem
      matrix results[1,2] = measuren
      matrix results[2,2] = diffmn
      matrix results[3,2] = pvaluemn
      foreach y in d pf {
        foreach b in m n {
          difgt y`b'_`x' y`y'_`x', alpha(`alpha') ///
            pline1(`PL`n'') pline2(`PL`n'')
          scalar measure`y' = r(est2) // pov for looped income measure
          scalar diff`b'_`y' = r(est3) // difference between market or net
            // market and looped income measure
          scalar pvalue`b'_`y' = 2*ttail(`N'-2, abs(r(est3)/r(std3)))
            // pvalue of difference
        } // end of b-loop
        matrix results[1,`y''] = measure`y' // note ``y'' uses the locals I
          // created earlier with the reverse tokenize loop
        matrix results[2,`y''] = diffm`y'
        matrix results[3,`y''] = pvaluem`y'
        matrix results[4,`y''] = diffn`y'
        matrix results[5,`y''] = pvaluen`y'
      } // end of y-loop
    }
    matrix colnames results = MARKET NET_MARKET DISPOSABLE POST-FISCAL
    matrix rownames results = P`alpha' Diff_wrt_Market (p-value) ///
      Diff_wrt_Net_Mkt (p-value)
    noisily matlist results, title("`alpha'") names(all) ///
      aligncolnames(ralign) nodotz underscore format(%11.4f) twidth(16) ///
      lines(columns) linesize(100)
  } // end of alpha-loop
}
```

```

    } // end n-loop for poverty lines
} // end quietly

```

Sheet D1 also asks for GDP, total disposable income according to the household survey, direct transfers (only those included in the analysis) according to national accounts, direct and in-kind transfers (again, only those included in the analysis) according to national accounts, direct transfers according to the household survey, direct and in-kind transfers according to the survey, and for the latter four, their counterparts when pensions are added in, for the sensitivity analysis. These are used for the effectiveness indicators, which are explained in the next section.

## ii. Sheet D2 – Effectiveness Indicators

The CEQ Effectiveness Indicator can be defined for any inequality or poverty measure of interest. In Table 1, we provide effectiveness indicators for the Gini coefficient and headcount index. The indicator is defined as the redistributive effect or effect on poverty of the transfers being analyzed divided by their relative size. Specifically, it is defined as follows for the Gini. Note that it would be similarly defined for any other inequality or poverty measure by replacing the word Gini with the appropriate measure. For direct transfers, the effectiveness indicator is the fall between the net market income and disposable income Ginis, divided by the size of direct transfers (only those included in the analysis) as a percent of GDP. We use *net market* rather than *market* income because we are measuring the effectiveness of *spending*; the difference between market and disposable income inequality or poverty would also include the impact of taxes. For direct and in-kind transfers, the effectiveness indicator is the fall between the net market income and final income\* Ginis as a percent of the net market income Gini, divided by the size of the sum of direct transfers (only those included in the analysis), education spending, health spending, and (where it was included in the analysis) housing and urban spending, as a percent of GDP. We use final income\* rather than final income again because we are measuring the effectiveness of *spending*; the difference between net market income and final income inequality would include the impact of indirect taxes.

In mathematical notation, let  $X(y^j)$  be the inequality or poverty measure of interest (e.g., the Gini coefficient or headcount index), which is defined at each benchmark case income concept  $y^j$  where  $j = m, n, d, pf, f^*, f$  (market income, net market income, disposable income, post-fiscal income, final income\* and final income) and each sensitivity analysis income concept  $j = ms, ns, ds, pfs, f^*s, fs$ . Let  $S^D$  be total public spending on the direct transfer programs captured by the survey or otherwise estimated by the authors, measured by budget size in national accounts (note that in the sensitivity analysis this concept includes spending in social security pensions, but in the benchmark case it does not), and let  $S^H$ ,  $S^E$  and  $S^U$  be total public spending on health, education, and (where included) housing programs, respectively. Then the effectiveness indicator for direct transfers is defined as:

$$\frac{(X(y^n) - X(y^d))}{S^D/GDP}$$

and the effectiveness indicator for direct and in-kind transfers is defined as:

$$\frac{(X(y^n) - X(y^{f*}))}{(S^D + S^H + S^E + S^U)/GDP}$$

We use absolute (percentage point) changes in the inequality or poverty measure rather than relative (percent) changes due to social welfare considerations.<sup>30</sup> In the case of inequality, Duclos and Araar (2006, p. 62) show that under commonly adopted assumptions about the social welfare function, we can use *equally distributed equivalent* (EDE) income—introduced by Atkinson (1969)—as our measure of social welfare. Since EDE income  $\xi$  can be written  $\xi = \mu(1 - I)$  where  $\mu$  is mean income and  $I$  is inequality, it is easy to see that (taking  $\mu$  as fixed), it is *absolute* rather than *relative* changes in inequality that matter in a social welfare context. In the case of poverty, consider a country with 40% poverty and a country with 2% poverty that both spend the same proportion of their GDP on anti-poverty programs and both reduce the proportion of the population living in poverty by half. The country with 40% poverty that reduces it to 20% has achieved a much more impressive increase in social welfare in the country than the country that begins with 2% and reduces it to 1%.

Note that in the sensitivity analysis, when contributory pensions are considered a government transfer, they are not part of net market income but are part of disposable income, thus some of the change between  $X(y^{ns})$  and  $X(y^{ds})$  is attributable to contributory pensions, and therefore in the sensitivity analysis  $S^D$  must include spending on contributory pensions. In the benchmark case, however, contributory pensions are already included in net market income, so  $S^D$  does not include any spending on contributory pensions. Also note that  $S^U$  should only be included in the denominator of the effectiveness indicator for direct and in-kind transfers if housing programs are included in the analysis, and it should only include the portion spent on those housing programs that are included.

The above equation gives the effectiveness indicator at the national level; for effectiveness indicators of sub-groups, such as in urban and rural areas or by race/ethnicity, the effectiveness indicator uses the inequality or poverty indicators for the sub-group only. The denominator must be adjusted for the amount of transfers reaching the sub-group and the amount of GDP corresponding to the sub-group, which are generally unavailable in national accounts so they are proxied by the proportion of transfers (direct transfers for the effectiveness indicator for direct transfers and direct and in-kind transfers for the effectiveness indicator for direct and in-kind transfers) reaching the subgroup according to the household survey, and the proportion of market income going to the sub-group, respectively. In other words, the sub-group effectiveness indicator for direct transfers is defined as

---

<sup>30</sup> We are grateful to Luis Servén for suggesting percentage point changes, and to Jean-Yves Duclos for explaining the connection with social welfare.



$$\frac{(X(y^n) - X(y^d))}{\left(\frac{D_g/D}{y_g^m/y^m}\right) \left(\frac{S^D}{GDP}\right)}$$

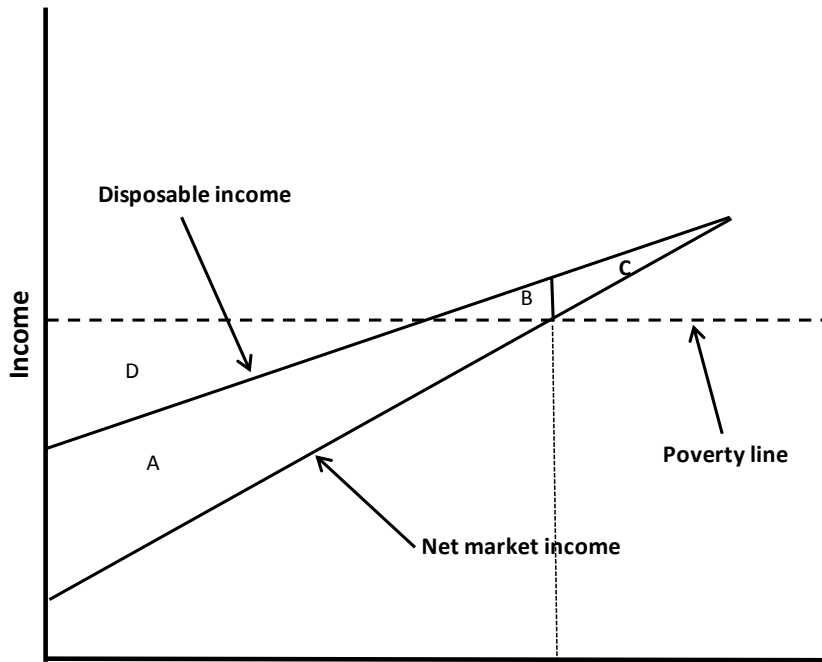
where  $D$  denotes total direct transfers according to the survey, the subscript  $g$  denotes the sub-group, and no subscript denotes the entire population. So, for example,  $y_g^m$  is total market income of sub-group  $g$ , and  $y^m$  is the total market income of the entire population. The effectiveness indicator for direct and in-kind transfers is defined analogously:  $S^D$  is replaced by  $S^D + S^H + S^E + S^U$  and  $D$  would be replaced by the total received in direct *and in-kind* transfers according to the survey.

The above describes the effectiveness indicator identified that we call “(national accounts)” because we use transfer budget sizes from national accounts and GDP for the denominator. The alternative effectiveness indicator, which we denote “(household survey)”, uses transfer sizes from the survey and, in place of GDP, total disposable income according to the survey.

The effectiveness indicators are calculated automatically once the orange cells on sheet D1 are filled in.

In addition to the CEQ Effectiveness Indicators, Sheet D2 includes a number of other effectiveness indicators developed by other authors. We use the three poverty-based effectiveness indicators from Beckerman (1979): vertical expenditure efficiency, poverty reduction efficiency, and spillover index, as well as poverty gap efficiency, which was added by Immervoll et al. (2009). Diagram 3 is intended to aid the explanation of these indicators.

### **Diagram 3. Additional Efficiency Indicators**



**Individuals ranked by household per capita market income**

Source: Adapted from Beckerman (1979).

The diagram is not to scale, nor are the income curves necessarily straight. In the diagram, total direct transfers is  $A+B+C$ , direct transfers reaching the net market income poor is  $A+B$ , the total net market income poverty gap is  $A+D$ , and the total disposable income poverty gap is  $D$ .

Beckerman (1979) then defines:

$$\text{Vertical expenditure efficiency} = (A+B)/(A+B+C)$$

$$\text{Spillover index} = B/(A+B)$$

$$\text{Poverty reduction efficiency} = A/(A+B+C).$$

Immervoll et al. (2009) additionally define:

$$\text{Poverty gap efficiency} = A/(A+D).$$

In more technical notation, we have:

$$\text{Vertical expenditure efficiency} = \frac{\sum_{\{i \mid y_i^n < z\}} (y_i^d - y_i^n)}{\sum_i (y_i^d - y_i^n)}$$

$$\text{Spillover index} = \frac{\sum_{\{i \mid y_i^n < z \leq y_i^d\}} (y_i^d - z)}{\sum_{\{i \mid y_i^n < z\}} (y_i^d - y_i^n)}$$

$$\text{Poverty reduction efficiency} = \frac{\sum_{\{i \mid y_i^d < z\}} (y_i^d - y_i^n) + \sum_{\{i \mid y_i^n < z \leq y_i^d\}} (z - y_i^n)}{\sum_i (y_i^d - y_i^n)}$$

$$\text{Poverty gap efficiency} = \frac{\sum_{\{i | y_i^d < z\}} (y_i^d - y_i^n) + \sum_{\{i | y_i^n < z \leq y_i^d\}} (z - y_i^n)}{\sum_{\{i | y_i^n < z\}} (z - y_i^n)}$$

where  $y_i^n$  is individual  $i$ 's household per capita net market income,  $y_i^d$  is individual  $i$ 's household per capita disposable income, and  $z$  is the poverty line. In the case of national poverty lines that vary by region, or the CEPAL poverty lines which vary depending on whether an individual lives in a rural or urban area,  $z$  in the above equations would simply be replaced by  $z_i$ , where the latter varies across individuals depending on their location. These effectiveness indicators can be calculated as follows for moderate poverty:

```
quietly {
local PPP = 1.7116 // PPP conversion factor for Brazil
local PPPyr = `PPP'*365 // divide by 12 if monthly
scalar z = 4*`PPPy` // $4 PPP poverty line in local currency per year
gen difference = yd_BC - yn_BC
gen pre_shortfall = z - yn_BC
gen post_shortfall = z - yd_BC
summarize difference [aw=s_weight] if yn_BC < z
scalar AB = r(sum)
summarize difference [aw=s_weight]
scalar ABC = r(sum)
summarize post_shortfall [aw=s_weight] if yn_BC < z & yd_BC >= z
scalar B = -r(sum)
summarize difference [aw=s_weight] if yd_BC < z
scalar A1 = r(sum)
summarize pre_shortfall [aw=s_weight] if yn_BC < z & yd_BC >= z
scalar A2 = r(sum)
scalar A = A1 + A2
summarize pre_shortfall [aw=s_weight] if yn_BC < z
scalar AD = r(sum)
scalar VEE = AB/ABC
scalar Spillover = B/AB
scalar PRE = A/ABC
scalar PGE = A/AD
noisily display "Vertical Expenditure Efficiency: " %7.6f VEE
noisily display "Spillover index: " %7.6f Spillover
noisily display "Poverty Reduction Efficiency: " %7.6f PRE
noisily display "Poverty Gap Efficiency: " %7.6f PGE
}
```

As a check, make sure that the Beckerman (1979) and Immervoll et al. (2009) indicators remain between 0 and 1.

Finally, we include commonly used tax productivity indicators from Gallagher (2005). These are as follows: (i) the number of taxes that comprise the top seventy-five percent of receipts; (ii) percentage of total taxpayers that provide seventy-five percent of tax receipts; (iii) total number of tax rates; (iv)

VAT rate; (v) indirect as percentage of total taxes; (vi) VAT collections as a percent of total tax collections; (vii) tax ratio, defined as the ratio of actual tax collections to GDP; (viii) administrative cost of taxation; (ix) gross compliance ratio, which is the actual VAT collection divided by potential VAT collection; and (x) VAT productivity, defined as the ratio of VAT collections to GDP divided by the nominal VAT rate.

### iii. Sheet D3 – Measures of Progressivity and Horizontal and Vertical Inequality

A useful summary statistic to measure progressivity is the Kakwani index (however, recall from Section 3 that concentration curves should also be used since the Kakwani index does not tell us when a concentration curve crosses the market income Lorenz curve or the 45 degree line). For taxes, the Kakwani (1977) index of progressivity can be thought of graphically as twice the area between the market income Lorenz curve and the tax concentration curve. If the tax concentration curve is above the Lorenz curve, the Kakwani index will be negative, which indicates that taxes are regressive in relative terms. Equivalently, the Kakwani index can be calculated as the tax's concentration coefficient (with the population ranked by market income) minus the market income Gini. In other words,  $K^{\text{tax}} = D_m^{\text{tax}} - G^m$ , where  $D_m^{\text{tax}}$  represents the concentration coefficient of a particular tax when the population is ranked by market income.

To adapt to the measurement of transfers, Lambert (1985) suggests that in the case of transfers it should be defined as market income Gini minus the concentration coefficient (i.e., the negative of the definition for taxes) to make the index positive whenever the change is progressive. Thus, we have  $K^{\text{transfer}} = -(D_m^{\text{transfer}} - G^m)$ , where  $D_m^{\text{transfer}}$  represents the concentration coefficient of a particular transfer when the population is ranked by market income.

Note that, because net taxes (i.e., taxes minus transfers) are negative for some individuals and positive for others, the concentration curve for net taxes will not be well-behaved (Lambert 2002). Hence, we calculate Kakwani indices separately for taxes and transfers without trying to group them into one category.

Sheet D3 asks for the Kakwani index for direct transfers, direct and in-kind transfers, direct taxes, indirect taxes, and all taxes. To capture the progressivity of direct transfers and taxes and indirect subsidies and taxes all combined, Sheet D3 also asks for the Reynolds-Smolensky index of post-fiscal income with respect to market income. Graphically, the Reynolds-Smolensky of post-fiscal income with respect to market income is twice the area between the market income Lorenz curve and the concentration curve of post-fiscal income with respect to the market income distribution. Note that the concentration curve of post-fiscal income is not the same as the Lorenz curve for post-fiscal income, as the concentration curve does not re-rank the population (population is still ranked by market income), whereas the Lorenz curve does re-rank the population (population would be re-ranked by post-fiscal income). Equivalently, the Reynolds-Smolensky can be calculated as the market income Gini minus the concentration coefficient of post-fiscal income when the population is ranked by market income. In other words,  $RS = G^m - D_m^{pf}$ , where  $D_m^{pf}$  represents the concentration coefficient of post-fiscal income when the population is ranked by market income.

The following sample Stata code, which uses the user-written command `concindexi` (written by Amadou Bassirou Diallo) to calculate both Ginis and concentration indices, can be used to calculate

the Kakwani and Reynold's Smolensky indices. Let the variable `directtrans` represent household per capita direct transfers, `transfers` direct and in-kind transfers, `directtax` direct taxes, `indirecttax` indirect taxes, and `alltax` all (direct plus indirect) taxes. The following code is for the benchmark case only, but could easily be looped over, as in the previous examples, to also produce results for the sensitivity analyses.

```
quietly {

* market income Gini
concindexi ym_BC [aw=s_weight], welfarevar(ym_BC) clean // clean option nec.
matrix Gini = r(CII)
scalar gini = Gini[1,1]

* kakwani: transfers
noisily display "KAKWANIS"
foreach tran in directtrans transfers {
  concindexi `tran' [aw=s_weight], welfarevar(ym_BC) clean
  matrix CC`tran' = r(CII)
  scalar D_`tran' = CC`tran'[1,1]
  scalar kakwani_`tran' = -(D_`tran' - gini)
  noisily display "`tran'"
  noisily display kakwani_`tran'
} // end transfers loop

* kakwani: taxes
foreach tax in directtax indirecttax alltax {
  concindexi `tax' [aw=s_weight], welfarevar(ym_BC) clean
  matrix CC = r(CII)
  scalar D_`tax' = CC[1,1]
  scalar kakwani_`tax' = D_`tax' - gini
  noisily display "`tax'"
  noisily display kakwani_`tax'
} // end of taxes loop

* reynolds-smolensky: post-fiscal
concindexi ypf_BC [aw=s_weight], welfarevar(ym_BC) clean
matrix RS = r(CII)
scalar rs = RS[1,1]
scalar reynoldssmolensky = gini - rs
noisily display "REYNOLDS SMOLENSKY"
noisily display "of post-fiscal income wrt market income"
noisily display reynoldssmolensky

} // end quietly
```

In addition to measuring progressivity, Sheet D3 decomposes a change in inequality into vertical and horizontal equity components. Vertical equity is concerned with the extent to which a policy equalizes incomes, and is thus closely linked to the measures of progressivity also on this output sheet. Horizontal equity, on the other hand, is concerned with how pre-policy equals are treated, postulating – in the classical definition of horizontal equity – that they should be treated equally. The re-ranking definition of horizontal equity differs slightly, postulating that the pre-policy income ranking should be preserved; for example, if individual A was poorer than individual B before policy

C, but receives enough transfer benefits from policy C that she becomes richer than individual B after policy C, there is horizontal *inequity*.<sup>31</sup> Duclos, Jalbert, and Araar (2003) propose a decomposition method that allows the change in the Gini coefficient between the before and after taxes and transfers scenarios into three components: vertical equity (the amount of inequality reduction that would be possible if the tax and transfer system treated equals equally), classical horizontal inequity (the increase in post-tax and transfer income inequality—relative to what could have been achieved—due to the unequal treatment of pre-tax equals), and the extent of reranking. Formally, following the notation of Duclos, Jalbert, and Araar (2003), let  $I$  denote inequality,  $I_X$  denote income inequality before taxes and transfers,  $I_N$  income inequality after taxes and transfers under the actual fiscal system,  $I_N^E$  income inequality after taxes and transfers if the fiscal system were horizontally equitable, and  $I_N^P$  income inequality after taxes and transfers if individuals were granted their expected after tax and transfer income utility. Then we can decompose the change in inequality,  $I_X - I_N = [I_X - I_N^E] - [I_N^P - I_N^E] - [I_N - I_N^P]$  where the first bracketed term is the vertical equity component  $V$ , the second is the classical horizontal inequity component  $H$ , and the third is the reranking component  $R$ .

The Duclos, Jalbert, and Araar (2003) decomposition can be undertaken with the user-written `dja` command (written by Abdelkrim Araar). To generate decomposition matrices similar to those on Sheet D3:

```
local xlist BC SA1 SA2 SA3
local postlist n d pf fstar f
foreach y of local postlist {
    local `y'=`i'
    local i=`i'+1
} // this loop makes locals n d pf fstar f that equal 1 2 3 4 5 which I
// use later to put my results in the results matrix (i.e. this loop does
// the equivalent of a reverse tokenize for `postlist')
foreach x of local xlist {
    display "Scenario: `x'"
    display ""
    matrix results = J(3,5,.)
    foreach y of local postlist {
        dja ym_`x' y`y'_`x' if i==1 // note: takes time with large dataset
        matrix results[1,`y''] = `r(V)'
        matrix results[2,`y''] = `r(H)'
        matrix results[3,`y''] = `r(R)'
    } // end loop over post-tax and transfer income vars
    matrix rownames results = V H R
    matrix colnames results = m_to_n m_to_d m_to_pf m_to_fstar m_to_f
    matlist results
    display ""
} // end loop over benchmark case, sensitivity
```

<sup>31</sup> A more thorough summary of vertical and horizontal equity can be found in Duclos (2008).

#### iv. Sheet D4 – Incidence by Decile and Socioeconomic Groups

The incidence sheet asks for the totals (in local currency per month or year) by decile and income group (defined above) of various categories of income components, as well as for each income definition. These totals are used to automatically generate incidence by decile or income group, which is defined as the total value of a particular income component or income concept received by a certain market income decile divided by the total market income of that same decile. The calculation is non-anonymous, meaning that we do not re-rank the population: the totals by decile that we are comparing are always by market income decile: in other words, we are measuring how much the incomes of identified individuals change when we add in certain income components.

Because many countries lack household survey data on direct transfers and have difficulty simulating them with accuracy, we also have a “Part B” of Sheet D4 that uses net market income, rather than market income, to define deciles and income groups, to ensure strict comparability across countries. Nevertheless, all countries should fill out both Part A and Part B if possible.

After creating deciles and income groups as explained in Section 2, the totals table can be generated using the `table` command with the `contents()` option, as shown below. Let the benchmark case market income deciles be saved as `ym_BC_decile`, household per capita benchmark case market and net market income `ym_BC` and `yn_BC`, respectively, household per capita direct taxes as `directtax`, and contributions to Social Security (only those directed towards things other than pensions, as explained in Section 2) as `contrib_to_SS_excl_pensions`. Taxes in this table should be entered as negative numbers. To display the first few columns of the incidence table, the commands would be:

```
preserve
local negatives directtax contrib_to_SS_excl_pensions // and other taxes
foreach var in local negatives {
    replace `var' = -`var' // make tax variables negative
}
table ym_BC_decile [pw=s_weight], contents(sum ym_BC sum directtax ///
    sum contrib_to_SS_excl_pensions sum yn_BC) row format(%16.0f)
    // this gives the first few columns of the table
restore // so that tax variables go back to being positive numbers
```

Similarly, the table that is separated by income groups rather than by deciles can be generated by replacing `ym_BC_decile` with the income group variable, e.g., `ym_BC_group`. The `row` option is used to provide a total for the population at the bottom of each column, and the `format()` option is used to ensure that the totals do not default to being expressed in scientific notation, since they are often large numbers.

Columns to the right of the main portion of the incidence table are included for tax exemptions and population. Tax exemptions are a form of subsidy, but they are already being accounted for in income in the form of lower taxes paid, so imputing them into people’s incomes as a subsidy would be double-counting. Nevertheless, we want to know how the amount received by each decile compares with their market incomes, so we add a separate column at the end for tax exemptions. The population totals serve two purposes: (i) they ensure that all deciles are approximately the same

size, and (ii) for income groups, they allow us to see how much each group receives in proportion to their population size.

#### v. **Sheet D5 – Concentration Shares by Decile and Socioeconomic Groups**

This sheet shows the concentration shares by decile or income group of the income components and concepts that were included in Sheet D4. In fact, it uses the data entered into the totals table on Sheet D4, so no additional data need be entered on Sheet D5; the sheet is automatically generated using Excel formulas.

Sheet D5 is again non-anonymous, meaning that deciles and income groups are always defined by one's market income (or net market income in the case of Part B, for the reasons explained under Sheet D4).

#### vi. **Sheet D6 – Income Distribution by Decile and Socioeconomic Groups**

In contrast with Sheet D5 in which individuals are ranked by initial household per capita market income (non-anonymous), in Sheet D6 the population is re-ranked at each income concept before we measure the total income of each decile or income group. When we use numbers from this sheet to measure changes in income, we are comparing, for example, the total income of the poorest *final income* decile with the market income of the poorest *market income* decile, even though these deciles are not necessarily composed of the same individuals. Standard measures of inequality, such as the Gini coefficient, and the FGT poverty indicators, are anonymous: i.e., we do not care about the previous rank or income level (sometimes called the 'reference point') of individuals. The information on this table can again be calculated using the `table` command, looping over income concepts:

```
foreach y in m n d pf fstar f {
  display "Income concept: `y'"
  table y`y'_BC_decile [pw=s_weight], contents(sum y`y'_BC) row ///
  format(%16.0f)
}
```

#### vii. **Sheet D7 – Fiscal Incidence Curves and Fiscal Mobility Profiles by Deciles**

Sheet D7 provides a graphical representation of some of the information contained in Sheets 4 and 6. It compares the incidence of transfers and taxes with “post-fisc” incomes, both without re-ranking (nonanonymous; Sheet D4) and with re-ranking (anonymous; Sheet D6). The former are analogous to the Income Mobility Profiles proposed by Van Kerm (2009) and will be called *Fiscal Mobility Profiles* (FMP). The anonymous fiscal incidence curves shall be called *Fiscal Incidence Curves* (FIC); they measure the anonymous redistribution induced by fiscal policy along the entire income distribution. Sheet D7 is based entirely on information entered in Sheets 4 and 6, and the graphs are generated automatically, so no additional information need be entered on Sheet D7.



**viii. Sheet D8 – Concentration Coefficients and Budget Shares for Social Spending and by Program**

Sheet D8 provides the concentration coefficients of individual transfer programs as well as aggregate categories such as Total Direct Transfers and CEQ Social Spending in Incidence Analysis. Let  $p$  be the cumulative proportion of the total population when individuals are ordered in increasing income values using market income, and let  $C(p)$  be the concentration curve, i.e., the cumulative proportion of total program benefits (of a particular program or aggregate category) received by the poorest  $p$  percent of the population. Then, the concentration coefficient of that program or category is defined as  $2 \int_0^1 (p - C(p)) dp$ . As discussed in Section 3, a program that is progressive in absolute terms will have a concentration curve above the line of perfect equality, and thus the area  $2 \int_0^1 (p - C(p)) dp$  will be negative, implying a negative concentration coefficient.

Note that concentration coefficients of transfers are calculated with respect to an income definition (market income in Part A and net market income in Part B) that does not include the transfer as one of its components. This makes theoretical sense, as we are aiming to judge how benefits are distributed with respect to people's ordering before taxes and transfers, not their ordering once they have received the benefit. Contributory pensions, however, *are* included in benchmark case market income, and we thus do not calculate their concentration coefficient with respect to benchmark case market income. To more clearly illustrate why, we note that Immervoll et al. (2009) show that the concentration coefficient for contributory pensions with respect to an income definition that includes contributory pensions can be higher than the market income Gini, signaling that they are regressive, whereas the Gini of market income net of pensions is higher than the Gini of market income with pensions, indicating that they are progressive. This seemingly contradictory occurrence is avoided by calculating all concentration coefficients of transfers with respect to pre-transfers income. Hence, we do not calculate the concentration coefficient of contributory pensions or CEQ Social Spending in Incidence Analysis plus Pensions with respect to benchmark case market income; instead, we include an additional column to calculate their concentration coefficients with respect to Sensitivity Analysis 1 market income, which does not include contributory pensions as one of its components.

Concentration coefficients and their standard errors (which also must be entered in Sheet D8) can be calculated using the user-written program `concindexi` (written by Amadou Bassirou Diallo), which allows a variable list, so the concentration indices for all variables can be calculated in one command. The following example loops over the benchmark case and sensitivity analyses (for the market income variable with respect to which the concentration coefficients are calculated). It additionally loops over using market and net market income as the pre-transfer income with respect

to which concentration coefficients are calculated, in order to fill out Parts A and B of the Master Workbook Template, respectively.

```
local m "Part A" // (this is just for organizational purposes so it is
local n "Part B" // easy to tell what corresponds to what)
foreach y in m n { // to loop over part A and part B
  display ""
  display "`y'" // displays Part A or Part B
  display ""
  foreach x in BC SA1 SA2 SA3 { // to loop over benchmark and sensitivity
    display ""
    display "`x'"
    concindexi varlist [aw=s_weight], welfarevar(y`y'_'x') clean
  } // end of x-loop
} // end of loop over parts A and B
```

where *varlist* would be replaced by the list of variables indicating the amount of benefits received from particular programs as well as aggregate categories.

Because the redistributive effect of a particular program is a function of both how progressive it is (measured by the concentration coefficient) and how large it is, Sheet D8 also asks for the budget sizes of each program. It asks for the budget size according to national accounts, which should be given net of administrative costs whenever possible, as well as the total income from that source, according to the household survey.

In an effort to be self-contained, Sheet D8 also asks for brief descriptions of all programs in the table, so that someone who is looking at the table can easily look up the details of a particular program, such as what type of transfer it is, its target population, and its conditions.

## ix. Sheet D9 – Coverage and Leakages by Program

Sheet D9 measures the coverage of the poor and those in other income groups, leakages to the non-poor, and average benefits per capita, per individual in a beneficiary household, and per transfer recipient. The distinction between the latter two deals with the question of how the “average transfer” should be calculated: because the transfer is added to aggregate household income which is then shared by everyone in the household, an economist would most likely measure the average transfer size among a particular income group as the total benefits received by that group divided by the number of individuals in that group who live in households that received the transfer. On the other hand, when the government reports the average transfer size, it usually reports the total spent on transfers divided by the number of transfer recipients, where a transfer recipient is defined as the individual who physically receives the transfer, and not individuals who live in the same household as a transfer recipient.

The majority of Sheet D9 is filled out automatically using formulas; the researcher must only fill out the total benefits received by group, number of individuals in beneficiary households by group, and number of recipients by group (individuals who report receiving the transfer, not other members of their household) for each individual program and broad category, as well as the market income totals and population totals by group. The individual programs and broad categories included in Sheet D9 are only examples; they should be replaced by the actual program names, and should be expanded upon. For example, if there are more than one conditional cash transfer (CCT) program, they should be listed in separate rows rather than under one aggregate row for CCTs. In addition, the researcher must enter the PPP conversion factor (row 121) and whether the totals are monthly or yearly (row 122) so that the average benefits can also be calculated in \$PPP per day.

From the total benefits by group and population totals entered by the researcher, the following are automatically calculated in the Master Workbook Template: share of benefits going to each income group (which can be used to determine what percent of benefits are leakages to the non-poor), share of individuals in beneficiary households in each income, percent of individuals in each group who live in beneficiary households (which can be used to determine coverage of the poor), average per capita benefits among beneficiary households by group, average benefits per capita by group, and average benefits per transfer recipient by group. The average benefits are calculated both in local currency and in \$PPP per day.

Total benefits received by group can be calculated in the same way that was demonstrated for broader income categories in Sheet D4 using the `table` command. Number of individuals in beneficiary households by group and number of recipients by group can be calculated multiple ways; one of the possibilities is discussed here. When constructing household aggregate income from each component, create a dummy variable that equals one for the individuals that report receiving income from that source, and zero for everyone else (including other members of their household that do not report that income source). Suppose for a particular program, this variable is called `dummy_program1`. The next step is to create a second dummy variable that equals one for each member of a household in which someone received a transfer. This can be accomplished as follows:

```
bysort hh_code: egen hh_dummy_program1 = max(dummy_program1)
```

where `hh_code` is the household identifier variable (i.e., it is a variable that has the same value for all members of the same household, and a different value for members of different households). The `max()` function looks for the maximum value of the input variable. When it is combined with `bysort`, it outputs the maximum value of the input variable among individuals with the same value for the variable listed after `bysort`. In this case, it outputs the maximum value of `dummy_program1` for individuals within the same household, so households in which no one is a program recipient (everyone has `dummy_program1 = 0`) will receive a value of zero for `hh_dummy_program1`, and households in which at least one member is a recipient (and thus has `dummy_program1 = 1`) receive a value of one for `hh_dummy_program1`. Then, these dummy variables can be used in combination

with the table command to count the number of transfer recipients and members of beneficiary households by group for each program as follows:

```
table ym_BC_group [pw=s_weight], contents(sum dummy_program1 ///
      sum hh_dummy_program1) row format(%16.0f)
```

Another measure of interest is the coverage and leakages of these programs among their target population. Thus, Sheet D9 also asks for the total benefits received by group of CCTs among households with children, non-contributory pensions and contributory pensions in households with a member over age 65, and education by level in households with children of the corresponding age. For education, the researcher should be sure to specify which ages were used by adding a note to the corresponding row on Sheet D9. For health, we measure the coverage of benefits other than preventative care with respect to the target population of those who were sick, if the survey has a question asking individuals if they were sick during the reference period. These totals are used to calculate the same measures listed above, except for the target population only.

#### x. Sheet D10 – Fiscal Mobility Matrices

As first shown in Higgins and Lustig (2013), standard incidence measures can fail to capture the extent to which some of the poor are further impoverished by the tax and benefit system. Hence, Sheet D10 reports the *impoverishment headcount index* (first proposed by Higgins and Lustig [2013]) which measures the percentage of the population who are *impoverished* by the tax and transfer system—in other words, they are either non-poor before taxes and transfers and made poor by the fiscal system, or they are poor before taxes and transfers and made even poorer by the tax and transfer system. Denoting income before taxes and transfers (i.e., market income) as  $y^0$ , income after taxes and transfers (disposable, post-fiscal, or final income) as  $y^1$ , the maximum poverty line as  $z$ , and the number of individuals in society as  $n$  the impoverishment headcount index is defined as  $n^{-1} \sum_{i=1}^n \mathbb{I}(y_i^1 < y_i^0) \mathbb{I}(y_i^1 < z)$  where  $\mathbb{I}(\cdot)$  is the indicator function, which has a value of 1 if its argument is true and 0 otherwise. The impoverishment headcount index is simple to calculate; below we provide sample Stata code for the case of benchmark case market to post-fiscal income using the \$4 PPP per day poverty line.

```
local PPP=1.7116 // PPP conversion factor for Brazil 2009 (consumption-based)
                  // from databank.worldbank.org
local PPPyr=`PPP'*365 // Brazil data is annual; if monthly also divide by 12
local PL = 4*`PPPy' // $4 PPP per day in local currency per year
gen impov = (ypf_BC<ym_BC & ypf_BC<`PL')
mean impov if i==1 [pw=s_weight]
```

Higgins and Lustig (2013) propose using the fiscal mobility matrix, which is a transition matrix that measures the proportion of individuals that move from a before taxes and transfers income group

(e.g., non-poor) to another income group (e.g., poor) after their income is changed by taxes and transfers. A transition matrix was first used to measure transition between income groups before and after taxes and transfers (Atkinson, 1980). Note that taxes and transfers can cause individuals to move up or down the income categories. The matrix in percents is row-stochastic, where rows represent before taxes and transfers income groups and columns represent after taxes and transfers income groups. Higgins and Lustig (2013) formally demonstrate the importance of the fiscal mobility matrix: standard measures fail to identify downward fiscal mobility among the poor caused, for example, by high consumption taxes. There are multiple matrices for the different possible definitions of post-tax income: for example, there is a mobility matrix for market to disposable income, as well as a mobility matrix for market to post-fiscal income. The mobility matrices have additional rows and columns concatenated to them to show the population shares by income group and the mean market income of that income group, for ease of reference.

To generate the fiscal mobility matrix, the researcher is asked for the total number of individuals in each  $(i, j)$  pair, where  $i$  is a pre-tax income group and  $j$  is a post-tax income group. The matrix of totals can be easily generated in Stata using the `tabulate` command. For example, for the benchmark case mobility matrix from market to post-fiscal income, the command would be:

```
tabulate ym_BC_group ypf_BC_group [iw=s_weight]
```

Mean market income by market and post-fiscal income groups (for the concatenated column and row, respectively) could be calculated with the following code.

```
foreach y in m pf {
    table y`y'_BC_group [pw=s_weight], contents(mean ym_BC) row format(%16.0f)
}
```

While the fiscal mobility matrix measures the proportion of the population that loses and gains enough to move to a higher income group, it does not capture the amount lost or gained (except to the extent that the amount lost or gained might be large enough to move more than one income group). Thus, the fiscal mobility matrix is complemented by income loss and income gain matrices, which measure the amount lost by those who lose and the amount gained by those who gain, respectively. One version of the loss and gain matrices is in average local currency lost or gained, and the other shows the average loss or gain as a proportion of before taxes and transfers income. The matrix also shows the average market income of the losers in pre-taxes and transfers income group  $i$  and post-taxes and transfers income group  $j$ , which serves as a useful reference point. The average loss in currency, average proportional loss, and average market income of losers in cell  $ij$  (as well as their counterparts in the gain matrices) can be calculated using the `table` command with the `contents` option, this time used with two variables after the command rather than one to create a two-way table. An if-condition determines who is included in the calculation: for the income loss (gain) matrix, only those who have lost (gained) income are considered, i.e., those who have post-taxes and transfers income that is lower (higher) than pre-taxes and transfers income. Thus, the

income loss (gain) matrix will be lower (upper) triangular by definition. The following code illustrates an example, where pre-taxes and transfers income is market income and post-taxes and transfers income is post-fiscal income.

```
* first create a local for the PPP factor since mean market incomes need to
* be in $PPP per day, per the Master Workbook Template's instructions
local PPP=1.7116 // PPP conversion factor for Brazil 2009 (consumption-based)
                // from databank.worldbank.org
local PPPyr=`PPP'*365 // Brazil data is annual; if monthly also divide by 12
foreach y in m pf {
    gen y`y'_BC_PPP = y`y'_BC/`PPPyr' // creates income variables in PPP/day
}

* variables for income loss or gain and proportional loss or gain
gen change = ypf_BC - ym_BC
gen change_proportional = (ypf_BC - ym_BC)/ym_BC

* average loss in local currency
table ym_BC_group ypf_BC_group if change<0 [iw=s_weight], contents( ///
    mean change)

* average proportional loss, mean market income in PPP
table ym_BC_group ypf_BC_group if change<0 [iw=s_weight], contents( ///
    mean change_proportional mean ym_BC_PPP)
```

## xi. Sheet D11 – Engel et al. (1999) Decomposition

Engel et al. (1999) provides a couple of very useful decompositions for our analysis. The first decomposes the change in a decile or socioeconomic group's concentration share of income before and after taxes and transfers<sup>32</sup> into a benefit component and a tax component. Specifically,

$$\lambda_i'' - \lambda_i = \frac{1 - \alpha}{1 - \alpha t} t \beta_i - \frac{t_i - \alpha t}{1 - \alpha t} \lambda_i$$

where  $\lambda_i$  ( $\lambda_i''$ ) is decile or group  $i$ 's income share before (after) taxes and transfers,  $\alpha \in [0,1]$  is the proportion of taxes that are not redistributed,  $t_i$  is the average effective tax rate paid by decile or group  $i$ ,  $\beta_i$  is the proportion of total transfers going to decile  $i$ , and  $t = \sum_i t_i \lambda_i$  is the average effective tax rate. Note that this decomposition is for non-anonymous income shares; in other words,  $i$  indexes groups where individuals are grouped by their *before* taxes and transfers income; if an individual is in group  $i$  before taxes and transfers, this individual is by definition also in group  $i$

---

<sup>32</sup> Recall that income concentration shares by decile and socioeconomic group were reported on Sheet D5.

after taxes and transfers, even if re-ranking took place and that individual would no longer belong to group  $i$  if we recalculated groups using after taxes and transfers income.

We illustrate with sample Stata code below for the case where before taxes and transfers income is taken to be market income and after taxes and transfers income is taken to be disposable income. In other words, in the example below, we are considering direct taxes and transfers only. The sample Stata code could easily be extended to different definitions of after tax and transfer income (i.e., post-fiscal and final income)—note that Sheet D11 asks for the decomposition for all three possible definitions of after taxes and transfers income. Suppose that all direct transfers have been grouped into a variable called `transfers` which has each individual's household per capita direct transfer amount, and that all direct taxes have been grouped into a variable called `taxes` which has each individual's household per capita direct taxes paid. The example below is by decile, but can be easily extended to an analysis by socioeconomic group.

```
quietly {

* lambda and lambda''
foreach y in m d { // loop over market and disposable income
    summarize y`y'_BC if i==1 [aw=s_weight] // benchmark case
    scalar total`y'_BC = r(sum)
    forval i=1/10 { // loop over deciles
        summarize y`y'_BC if ym_BCdecile==`i' & i==1 [aw=s_weight]
        scalar total`y'_BC_`i' = r(sum)
        lambda`i'_`y' = total`y'_BC_`i'/total`y'_BC
    }
}

matrix results = J(10,7,.)
matrix colnames results = lambda_i_before lambda_i_after difference t_i ///
                        beta_i transfers_term taxes_term
forval i=1/10 { // loop over deciles
    matrix results[`i',1] = lambda`i'_m
    matrix results[`i',2] = lambda`i'_d
    matrix results[`i',3] = lambda`i'_d - lambda`i'_m
}

* t and alpha
foreach x in taxes transfers {
    summarize `x' if i==1 [aw=s_weight]
    scalar total`x' = r(sum)
}

scalar alpha = (totaltaxes - totaltransfers)/totaltransfers
noisily display as text "alpha = " %5.4f alpha
scalar t = totaltaxes/totalm_BC
noisily display as text "t = " %5.4f t

* t_i, beta_i, transfers term, and taxes term
* (note transfers term is first term on right hand side of the equation
* above, taxes term is second term)
```

```

forval i=1/10 { // loop over deciles
  foreach `x' in taxes transfers {
    summarize `x' if decile==`i' & i==1 [aw=s_weight]
    scalar total`x'`i' = r(sum)
  }
  scalar t`i' = totaltaxes_`i'/totalm_BC_`i' // tax by decile divided by
  // market income of that decile (= average effective tax rate of decile)
  scalar beta`i' = totaltransfers_`i'/totaltransfers // proportion of
  // total benefits going to that decile
  matrix results[`i',4] = t`i'
  matrix results[`i',5] = beta`i'
  matrix results[`i',6] = ((1-alpha)/(1-(alpha*t)))*t*beta`i'
  matrix results[`i',7] = ((t`i'-alpha*t)/(1-(alpha*t)))*lamda`i'
} // end deciles loop

noisily matlist results // display matrix of results
} // end quietly

```

The second decomposition is to decompose a change in the Gini coefficient, which can be shown to depend on just five parameters: the average effective tax rate  $t$ , the losses to deadweight loss or the “leaky bucket” during the redistribution process,  $\alpha$ , the concentration of benefits represented by the Gini coefficient of benefits,  $G_\beta$ , the concentration of taxes represented by the Gini coefficient of taxes,  $G_{\lambda t}$ , and the initial Gini coefficient before taxes and transfers,  $G$ . If we denote the change in the Gini coefficient by  $\Delta G$ , then the decomposition can be written

$$\Delta G = \frac{-t}{1-\alpha t} [(1-\alpha)G_\beta + G_{\lambda t} - \alpha G]$$

Note that the proof of this decomposition only works if absolute taxes are everywhere non-decreasing in market income and the proportion of benefits received is everywhere decreasing in market income. In practice, this is unlikely to hold at the individual level, but likely to hold for deciles, and possibly for smaller groups such as percentiles. Below, our sample Stata code attempts the analysis at the percentile level; the user must check to make sure these conditions hold. Note that this implies the Ginis calculated below will be approximations which ignore intra-percentile inequality.

```

quietly {
  quantiles ym_BC if i==1 [aw=s_weight], n(100) k(hh_code) gen(ym_BCcent)
  preserve
  sort ym_BCpercentile
  collapse (mean) ym_BC yd_BC transfers taxes if i==1 [aw=s_weight] ///
    , by(ym_BCcent) // makes 100-obs data set with percentile averages
  concindexi ym_BC, welfarevar(ym_BC) clean
  matrix G_matrix = r(CII)
  scalar G = G_matrix[1,1]
  concindexi transfers, welfarevar(transfers) clean
}

```



```

matrix G_beta_matrix = r(CII)
scalar G_beta = G_beta_matrix[1,1]
concindexi taxes_s, welfarevar(taxes) clean
matrix G_lambdat_matrix = r(CII)
matrix G_lambdat = G_lambdat_matrix[1,1]
noisily display as text "t = " %5.4f t // this was calculated in earlier code
noisily display as text "alpha = " %5.4f alpha // ditto
noisily display as text "G_beta = " %5.4f G_beta
noisily display as text "G_lambdat = " %5.4f G_lambdat
noisily display as text "G = " %5.4f G
restore
} // end quietly

```

Now, by placing the above results in Sheet D11, the user can make marginal changes to one of the parameters to calculate how a marginal change in that parameter would affect the decrease in inequality due to taxes and transfers.

### xiii. Sheet D12 – Needs vs. Resources

This sheet compares the amount of money that would be required to eliminate income, health, and education poverty (assuming perfect coverage and targeting) compared with the amount of resources available. It can be very useful when answering the Diagnostic Questionnaire which asks a number of questions that compare needs to resources. The table consists of a “full table” and a “summary table”; the summary table is filled out automatically using Excel formulas based on inputs entered into the full table. Since needs are measured before and after taxes and transfers, there are four scenarios considered: before transfers is market income and after transfers is disposable income; before transfers is market income and after transfers is post-fiscal income; before transfers is net market income and after transfers is disposable income; and before transfers is net market income and after transfers is post-fiscal income. The various elements of Sheet D12 are defined in turn. For simplicity, the definitions below are for the first scenario (before transfers is market income and after transfers is disposable income), but they can be easily adapted to the additional scenarios.

#### *Income Poverty Gap*

This is equal to the total shortfall of the poor’s incomes below the poverty line. This total is *not* normalized by the poverty line or divided by the population, as it was in Sheet D1 to calculate the poverty gap *index*. Continuing the notation used under Sheet D1, denote  $g_i = z - y_i$  the income shortfall of individual  $i$  (i.e., the increase in income that would be required for individual  $i$  to no longer be poor),  $q$  denote the number of poor individuals (using whichever income concept is being used), and let the population be ranked by the income concept being used from poorest to richest. Then the income poverty gap is defined as  $\sum_{i=1}^q g_i$ . The before transfers income poverty gap uses market or net market income, and the after transfers income poverty gap uses disposable or post fiscal income.

For the benchmark case full table where before transfers income is taken to be market income and after transfers income is taken to be disposable income, the income poverty gap could be calculated in Stata as follows:

```

local PPP=1.7116 // PPP conversion factor for Brazil 2009 (consumption-based)
                  from databank.worldbank.org //
local PPPyr=`PPP'*365 // Brazil data is annual; if monthly also divide by 12
local lines 125 250 400 1000 5000 // $1.25 etc. but won't work with decimals
foreach n in `lines' {
    local PL`n'=(`n'/100)*`PPPyr'
}
foreach n in 250 400 {
    capture drop before_shortfall after_shortfall
    gen before_shortfall = (ym_BC < `PL`n')*(`PL`n' - ym_BC) // note
    summarize before_shortfall if i==1 [aw=s_weight]
    scalar before_gap = r(sum)
    display "Before transfers income poverty gap = " %20.0f before_gap
    // the %20.0f formats that the output not be in scientific notation as
    // long as it is less than 20 digits, and that it round to the nearest
    // integer - see help format
    gen after_shortfall = (yd_BC < `PL`n')*(`PL`n' - yd_BC)
    summarize after_shortfall if i==1 [aw=s_weight]
    scalar after_gap = r(sum)
    display "After transfers income poverty gap = " %20.0f after_gap
}

```

The line labeled “note” deserves some explanation. First, we have created locals PL250 and PL400 which equal the \$2.50 and \$4 PPP per day poverty lines in local currency per year (the same monetary units as our data); when Stata sees the term ``PL`n''` it first replaces the inner ``n'`` with either 250 or 400, then replaces ``PL250'`` or ``PL400'`` with the appropriate poverty line, saved as a local. To the right of the equals sign, the first term in parentheses is how indicator functions—written as  $\mathbb{I}(\cdot)$  or  $1(\cdot)$  in the literature—are written in Stata. In other words, the term `(ym_BC < `PL`n')` is essentially a dummy variable: it will equal zero for individuals who are not market income poor and will equal the distance between their incomes and the poverty line (the second term in parentheses) for those who are market income poor.

#### *Before Transfers Education Poverty Gap*

The before transfers education poverty gap is defined as the total annual cost of educating the poor. It is calculated by dividing the annual public spending on education at level  $l$  from national accounts by the number of students at level  $l$  from national accounts (or, equivalently, obtaining spending per student by level from national accounts), multiplying that by the number of children who are in the age range that corresponds to education level  $l$  and are market (or net market) income poor, then summing over all  $l$ , where  $l$  are the

education levels, e.g., primary, lower secondary, upper secondary. Poor children who are not enrolled in school are included in the calculation of total demand for education among the market income poor, and treated as belonging to the level to which their age corresponds. Poor children who are enrolled in school but are behind their age level are treated as belonging to the level that corresponds to their age, not the actual level in which they are enrolled. The critical ages for schooling are from six to eighteen years old, so children under six years old or over eighteen years old are not included in the calculation. The critical level of schooling is twelve years, so individuals who have already completed twelve years of schooling are not included in the calculation.

#### *After Transfers Education Poverty Gap*

The after transfers education poverty gap is calculated similarly to the before transfers education coverage gap, but instead of multiplying the spending per student by level by the total number of market (or net market) income poor students at that level, it is multiplied by the number of market (or net market) income poor students at that level *who are not enrolled in school*.

#### *Before Transfers Health Poverty Gap*

The before transfers health poverty gap is defined as the total cost of providing basic health coverage to the poor. From public accounts or national health accounts, obtain the cost of a basic health package. Multiply this by the total number of market (or net market) income poor.

#### *After Transfers Health Poverty Gap*

The after transfers health poverty gap is calculated similarly to the before transfers health poverty gap, except instead of multiplying the cost of a basic health package times the number of market (or net market) income poor, it is multiplied by the number of market (or net market) income poor who are not covered by the public health insurance scheme. If data on health coverage is not available or if the country does not have a public health insurance scheme, the after transfers health poverty gap can be defined based on use; in that case, the after transfers health poverty gap is defined as the before transfers health poverty gap minus total in-kind health benefits received by the market (or net market) income poor. The latter is calculated as described in the Income Concepts and Data Requirements section.

#### *Human Capital Poverty Gap*

The before (after) transfers human capital poverty gap is the sum of the before (after) transfers education poverty gap and the before (after) transfers health poverty gap.

#### *Overall Poverty Gap*

The before (after) transfers overall poverty gap is the sum of the before (after) transfers income poverty gap and the before (after) transfer health poverty gap.

### *Total Government Spending*

Total government spending according to public sector accounts. It should include all social spending, all administrative spending, spending on housing, water, sanitation, etc., spending on economic subsidies, servicing external debt, military spending, etc. It should include both recurrent spending and investment spending (e.g., in education, health, and infrastructure). If you are including subnational spending and taxes in your study, it should include subnational spending. Write down a specific definition of total government spending used in your study and specify whether it is federal/central only or the latter plus subnational. Remember to document the source/s with specific locations of from where the data came.

### *Primary Government Spending*

Primary government spending is equal to total government spending net of domestic and external debt servicing.

### *Total Government Revenue*

Total government revenues include the total budgetary income of the federal/central government: tax and non-tax revenue plus income generated by direct budgetary controlled entities or public enterprises. In countries where revenue collected at the provincial or state level is important, the total should include the revenues obtained by governments at the subnational level if possible. Specify whether subnational revenue is included.

### *Targeted Anti-Poverty Spending*

Targeted anti-poverty spending includes direct transfers programs that by design use a mechanism to target benefits to the poor.

### *Reaching the poor*

Resources reaching the poor is calculated using the household survey, since this information is not available in national accounts.

## **xiii. Sheet D13 – Cumulative Distribution Functions of Income**

This set of graphs shows the cumulative distribution functions (CDFs) of benchmark case market, net market, disposable, and post-fiscal income. The cumulative distribution function (CDF) of income is then defined as  $\int f(y^j)dy$  where  $f(y^j)$  is the density function of income concept  $j$ . Hence, the CDF is anonymous by definition: the underlying distribution is ranked by whatever income concept is being measured, rather than maintaining the original market income ranking. Following Atkinson (1987) and Foster and Shorrocks (1988), if one income concept first order stochastic dominates another (i.e., its CDF lies everywhere below the other's) over a domain of poverty lines, then the headcount index is unambiguously lower for the first income concept over that domain of poverty lines. With respect to other poverty measures beyond the headcount index, if one income concept first order stochastic dominates another over the range of poverty lines from 0

to a maximum poverty line, then poverty is unambiguously lower in the first income concept for any poverty measure that is continuous, non-decreasing in income, and additively separable. In the case where first order stochastic dominance is not found (i.e., the CDFs of two income concepts cross), poverty can still be unambiguously lower in one of the income concepts if the poverty measure is distribution-sensitive such as the squared poverty gap. More specifically, if one income concept second order stochastic dominates another (i.e., if the integral under its CDF is less than that of the other) from 0 to a maximum poverty line, then poverty is unambiguously lower in the first income concept for any poverty measure that is continuous, non-decreasing in income, and concave in income (Atkinson, 1987).

The graphs of income CDFs can be generated using our user-written `incomecdf` (written by Sean Higgins) which can be downloaded from within Stata by typing `ssc install ceq`. After it is installed, type `help incomecdf` to see the help file.<sup>33</sup> By default, `incomecdf` produces five income CDF graphs with various levels of “zooming in” along the x-axis, which is the axis measuring income, with the following domains: (i) \$0 to \$2.50 PPP; (ii) \$0 to \$4 PPP; (iii) \$0 to \$10 PPP; (iv) \$0 to \$50 PPP; (v) \$0 to \$100 PPP. There are two possible syntaxes: the first is to convert the income variables in local currency into \$PPP per day, and use those variables in the variable list, as follows:

```
local PPP=1.7116 // PPP conversion factor for Brazil 2009 (consumption-based)
                  from databank.worldbank.org //
local PPPyr=`PPP'*365 // Brazil data is annual; if monthly also divide by 12
foreach y in m n d pf {
    gen y`y'_BC_PPP = y`y'_BC/`PPPyr' // creates income variables in PPP/day
}
incomecdf ym_BC_PPP yn_BC_PPP yd_BC_PPP ypf_BC_PPP [aw=s_weight]
```

The second option is to use income in local currency (which could be in daily, monthly, or yearly terms), then to specify the consumption-based PPP conversion factor and whether the data is daily, monthly, or yearly as options, as follows:

```
incomecdf ym_BC yn_BC yd_BC ypf_BC [aw=s_weight], ppp(1.7116) yearly
```

where `yearly` can be replaced by `monthly` or `daily`. The `incomecdf` program also includes a number of graphing options: the axis titles, graph title, and graph subtitle can be changed using the options `ytitle()`, `xtitle()`, `graphtitle()`, and `subtitle()`. The defaults are “Cumulative percent of the population” for `ytitle()`, “Income in \$ PPP per day” for `xtitle()`, and no title or subtitle. The line width can be adjusted using the option `lwidth()` (type `help linewidthstyle` to see the choices for `lwidth()`), the colors of the lines can be changed using the option `colors()`, the format of the legend can be edited using the option `legend()` in combination with the normal syntax for `legend()` in Stata’s graphing commands (`help legend_option`), and the graphs can be

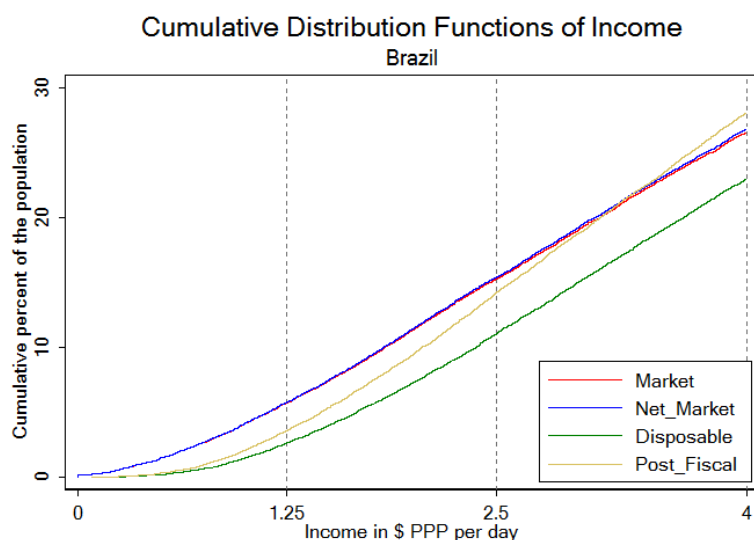
---

<sup>33</sup> To download this program from within Stata, type `ssc install ceq`. To see the help file, `help incomecdf`.

suppressed with the option `nodraw`. By default, the graphs are saved as `CDF250.gph`, `CDF400.gph`, etc. in the working directory, and can be viewed by typing e.g. `graph use CDF250.gph`. For example, Figure 1 shows the \$0 to \$4 PPP per day graph generated by the syntax

```
label var ym_BC Market
label var yn_BC Net_Market
label var yd_BC Disposable
label var ypf_BC Post_Fiscal
set scheme slcolor
incomecdf ym_BC yn_BC yd_BC ypf_BC [aw=s_weight], ppp(1.7116) yearly ///
  title("Cumulative Distribution Functions of Income") subtitle("Brazil") ///
  colors(red blue green sand) legend(position(5) ring(0) cols(1)) ///
  nodraw
graph use CDF400.gph
```

**Figure 1. Example graph from `incomecdf` program**



#### xiv. Sheet D14 – Lorenz Curves and Concentration Curves

This sheet graphs the Lorenz curves for each income definition and concentration curves for the main spending and tax categories. The latter are calculated with respect to the market income distribution. For each scenario (Benchmark Case, Sensitivity Analysis 1, etc.), the researcher should provide one graph of Lorenz curves and one graph of concentration curves.

The Lorenz curve maps the cumulative share of income (using whichever income concept the curve corresponds to) on the vertical axis against the cumulative share of the population, ordered by income (using whichever income concept the curve corresponds to), on the horizontal axis. Because the horizontal axis is re-ranked with each income concept, the Lorenz curve is an anonymous measure by definition; its non-anonymous analog would be the concentration curve of each income

definition with respect to the market income rankings. For income concept  $j$ , the Lorenz curve is defined as

$$L_j(p) = \frac{1}{\bar{y}^j} \int_0^{F^{-1}(p)} y^j dF(y^j) \text{ for } p \in [0,1]$$

where  $\bar{y}^j$  is mean income,  $F(y^j)$  is the cumulative density function of income, and  $p$  is the proportion of the population.

The concentration curve (sometimes called a quasi-Lorenz curve) maps the cumulative share of benefits received or taxes paid from a particular category of transfers or taxes on the vertical axis against the cumulative share of the population, ordered by market income, on the horizontal axis. The progressivity of a tax or transfer can be determined by comparing its concentration curve to the market income Lorenz curve, as shown in Diagram 2 (Section 3). Whether a progressive transfer is progressive in absolute terms or relative terms, in turn, can be determined by comparing the concentration curve to the 45 degree line. Thus, the concentration curves graph includes the 45 degree line, the market income Lorenz curve, and concentration curves for the following categories of transfers and taxes: direct taxes, direct transfers, indirect subsidies, indirect taxes, in-kind education, and in-kind health. In Sensitivity Analysis 1 only, the figure for direct taxes should include contributory pensions. For tax or transfer  $t$ , the concentration coefficient with respect to market income is defined as

$$C_t(p) = \frac{1}{\bar{t}} \int_0^{F_m^{-1}(p)} t dF_m(t) \text{ for } p \in [0,1]$$

where  $\bar{t}$  is the mean of the tax or transfer over the population (including those who do not receive the transfer or pay the tax),  $F_m(c)$  is the cumulative density function of transfer  $t$  with respect to the market income distribution, and  $p$  is the proportion of the population.

In Stata, the user-written command `glcurve` (written by Philippe van Kerm) can be used to graph Lorenz curves (to install, type `ssc install glcurve` in the command box of Stata); however, the command does not allow users to graph multiple Lorenz curves on the same graph without a bit of programming. As illustrated below, one can use `glcurve` with the `nograph` option to generate a set of coordinates for each observation in the data set which marks where that observation lies on the Lorenz curve. Additionally, the option `lorenz` is used to generate coordinates for the Lorenz -- rather than generalized Lorenz -- curve. After obtaining coordinates corresponding to each income concept, one can graph all curves on the same graph using the Stata graphing command `twoway`, as illustrated below. Concentration curves are generated similarly, adding the `sortvar()` option to tell Stata the variable with respect to which we are measuring concentration (i.e., market income).

The following sample code is for the benchmark case only, but graphs should also be produced for each sensitivity analysis. As always, let the variables `y*_BC` represent benchmark case income variables. Let the variables `directtax`, `directtrans`, `indirectsubs`, `indirecttax`, `educ`, and `health` represent variables for the corresponding tax and transfer programs.

```
* for Lorenz curves:
foreach y in m n d pf f {
  quietly glcurve `y' y*_BC [aw=s_weight], ///
    lorenz pvar(`y'x) glvar(`y'y) nograph replace
  local L_graphlist "`L_graphlist' (line `y'y' `y'x [pw=s_weight], sort)"
}

* for concentration curves:
foreach c in directtax directtrans indirecttax indirectsubs educ health {
  quietly glcurve `c' [aw=s_weight], ///
    sortvar(ym_BC) lorenz pvar(`c'x) glvar(`c'yaxis) nograph replace
  local cc_graphlist "`cc_graphlist' (line `c'y' `c'x [pw=s_weight], sort)"
}

* for 45 degree line:
gen diagline = my
label var diagline "45 Degree Line"

* for legends:
label var my "Market Income"
label var ny "Net Market Income"
label var dy "Disposable Income"
label var pfy "Post-fiscal Income"
label var fy "Final Income"
label var directtaxy "Direct Taxes"
label var directtransy "Direct Transfers"
label var indirectsubsy "Indirect Subsidies"
label var indirecttaxy "Indirect Taxes"
label var educy "In-kind Education"
label var healthy "In-kind Health"

* graph settings:
set scheme slcolor // sets the graph formatting scheme
local options legend(ring(0) pos(11) style(column)) ///
  xscale(range(0 1)) yscale(range(0 1))

* graphs:
twoway ///
  (line diagline diagline [pw=s_weight], sort clcolor(gray)) ///
  `L_graphlist' ///
  , ///
  ytitle("Cumulative proportion of income") ///
  xtitle("Cumulative proportion of the population") ///
  `options' ///
```



```

    saving(L_graph, replace) // L_graph.gph will be file name of graph
twoway ///
    (line diagline diagline [pw=s_weight], sort clcolor(gray)) ///
    (line my mx [pw=s_weight], sort) ///
    `cc_graphlist' ///
    , ///
    ytitle("Cumulative proportion of tax or transfer") ///
    xtitle("Cumulative proportion of the population") ///
    `options' ///
    saving(c_graph, replace) // c_graph.gph will be file name of graph

```

Note that the graphs in .gph format can only be read by Stata; to import them into Excel, it is best to convert them to a .png file as follows. If the following method produces pixelated picture files, add the `width()` and `height()` options to the `graph export` command to increase the picture size when exporting it to a .png file.

```

* to save graphs as .png (picture) files:
foreach graphname in L_graph c_graph {
    graph use `graphname'
    graph export `graphname'.png, replace
    graph drop _all
}

```

## xv. Sheet D15 – Inequality of Opportunity<sup>34</sup>

Sheet D15 measures ex-ante inequality of opportunity based on circumstances sets.<sup>35</sup> First, circumstances sets are identified: for example, one circumstances set could be {female, black, parents were college graduates, urban}: all individuals with those four traits are grouped together in that circumstances set. Circumstances are pre-determined factors that are not dependent on an individual's effort, such as race, gender, and parents' education or parents' income. Once each individual's circumstances set has been identified, the mean income of each circumstances set (i.e., the mean income of all individuals in that circumstances set) is calculated for each income concept. Benchmark case income is used for each income concept. Let  $s_i^j$  indicate the mean income for income concept  $j$  of everyone in individual  $i$ 's circumstances set. Each individual is attributed the mean income of their circumstances set, and this income distribution is called the smoothed income distribution. Inequality measured over the smoothed income distribution for each income concept uses the mean log deviation, which gives the measure of inequality of opportunity in levels by income concept. Dividing the resulting measure by the mean log deviation for the original income distribution measures the ratio of inequality due to inequality of opportunity as opposed to inequality of effort. The latter, called inequality of opportunity in ratios on Sheet D15, traces out how each redistributive step affects inequality of opportunity. For example, if the proportion of

<sup>34</sup> This section is based on a brief description of inequality of opportunity sent to the authors by Norbert Fiess.

<sup>35</sup> See Checchi and Peragine (2010) and Ferreira and Gignoux (2011).

inequality explained by unequal opportunities decreases from net market to disposable income but increases from disposable to post-fiscal income, this would indicate that direct transfers have an equalizing impact on ex ante opportunities, but indirect taxes and subsidies have an unequalizing effect.

The mean log deviation of the smoothed distribution (for income concept  $j$ ) is calculated as

$$\frac{1}{n} \sum_i \ln \left( \frac{\mu^j}{s_i^j} \right)$$

where  $\mu^j$  is the mean income of the population for income concept  $j$  (either the original or smoothed distribution can be used to calculate  $\mu^j$  since they have the same mean by definition), and  $s_i^j$  is defined above.

Inequality of opportunities in levels and trends can be calculated by the user-written `oppincidence` available from the within Stata (written by Sean Higgins),<sup>36</sup> using the following syntax.

```
oppincidence ym_BC yn_BC yd_BC ypf_BC yf_BC [aw=s_weight], ///
    groupby(male race fathers_education mothers_education rural)
```

where the variable list immediately following `oppincidence` lists all the income concepts over which inequality of opportunities is being calculated, and the required argument `groupby()` gives the categorical variables used to determine circumstances sets. Note that, since the variables used to determine circumstances sets must be categorical rather than continuous, variables such as `fathers_education` and `mothers_education` have to be given as categories (i.e., 1 = never attended school, 2 = primary incomplete, 3 = primary complete, etc.) rather than as years of schooling completed.

## **xvi. Sheet D16 – Progressiveness of Pensions**

This sheet summarizes the progressiveness of pensions and CEQ Social Spending, and will be used to construct multi-country summary tables. All of the elements of this sheet are generated automatically using Excel formulas based on inputs from other parts of the Master Workbook Template.

## **xvii. Sheet D17 – Comparison over Time**

Although CEQ is initially completed for a particular year, subsequent analysis can entail completing the analysis for multiple survey years.<sup>37</sup>

---

<sup>36</sup> To download this program from within Stata, type `ssc install ceq`. To see the help file, `help oppincidence`.

For analyses over time, we propose a simple but new decomposition of the change in the disposable income Gini into a change in the pre-intervention (market income) Gini and a change in the level of redistribution, as follows.

Let  $G_m^t$  and  $G_d^t$  be the market and disposable income Gini in year  $t$ , respectively; and  $G_m^{t'}$  and  $G_d^{t'}$  be the market and disposable income Gini in year  $t'$ . Denoting  $R^t$  and  $R^{t'}$  the portion of the change from market income Gini to disposable income Gini, we can write:

$$G_d^t = G_m^t - R^t$$

and

$$G_d^{t'} = G_m^{t'} - R^{t'}$$

Subtracting the latter from the former yields:

$$(G_d^{t'} - G_d^t) = (G_m^{t'} - G_m^t) - (R^{t'} - R^t)$$

or

$$(R^{t'} - R^t) = (G_m^{t'} - G_m^t) - (G_d^{t'} - G_d^t)$$

So,  $(R^{t'} - R^t)$  is the portion in the change in disposable income Gini between two points in time that can be attributed to a change in the redistribution component (in comparison to the change in market income Gini).

### xviii. Sheet D18 – Comparison with Other Studies

The final sheet consists of comparing the results from the incidence analysis with the results from other studies (incidence analyses in particular) for the same country. A thorough comparison table is included as an example in the Master Workbook Template.

## Appendix A. Correcting for Underestimating Number of Beneficiaries

---

<sup>37</sup> Examples of CEQ studies that have completed the analysis for multiple years are Lustig and Pessino (2013), Scott (2013), and Lopez-Calva, Lustig, Scott, and Castañeda (2013).

(Waiting on permission from Sergei Soares to use code adapted from the code he sent us. In the meantime we have this as a stand-alone appendix which will be available to country teams but will not be published as part of the working paper.)

## Appendix B. Definition of Household: Sensitivity Tests

The following table, provided by the Centro de Estudios Distributivos Laborales y Sociales (CEDLAS), shows that poverty and inequality results are not very sensitive to the definition of the household (i.e., the choice of whether to exclude renters, domestic servants, and their families; to include them as separate households; or to include them as part of the main household).

**Table B.1. Poverty and Inequality with Different Household Definitions**

	Households	Observations with ipcf	Members	ipcf	itf	Poverty 2.5 USD a day	Poverty 4 USD a day	Gini
<b>Argentina 2011</b>								
SEDLAC	34,298	110,785	3.163	2,340.13	7,391.39	4.7	10.8	0.423
Alternative 1	34,298	110,850	3.164	2,337.96	7,400.84	4.7	10.9	0.423
Alternative 2	34,359	110,850	3.158	2,340.21	7,391.13	4.7	10.8	0.422
<b>Brazil 2011</b>								
SEDLAC	117,796	346,021	3.024	824.16	2,487.60	12.6	24.5	0.527
Alternative 1	117,796	346,797	3.031	824.53	2,494.24	12.6	24.4	0.527
Alternative 2	118,453	346,807	3.015	824.56	2,481.36	12.6	24.4	0.527
<b>Mexico 2010</b>								
SEDLAC	27,665	104,493	3.873	2,720.75	10,525.58	12.5	28.0	0.474
Alternative 1	27,665	104,633	3.878	2,717.32	10,525.58	12.5	28.0	0.473
Alternative 2	27,771	104,585	3.862	2,724.90	10,523.00	12.5	28.0	0.474

**Alternative 1:** including domestic servants, their families and renters as household members of the main household

**Alternative 2:** domestic servants, their families or renters as separate households

*Source:* Centro de Estudios Distributivos Laborales y Sociales (CEDLAS)

## Appendix C. Predicting Rent to Impute the Value of Owner Occupied Housing

### *Introduction*

Families that own their homes earn implicit income that they would otherwise be paying in rent. This implicit income must be added to their total income if income is being used as an indicator of welfare, such as in poverty and inequality analyses. As an example, a household with income of 100 currency units per month that owns its home is better off than a household with the same income

that must then pay 30 currency units per month in rent, all else equal. Since expenditures are not removed from income before estimating poverty and other income-based indicators, both households would have income of 100 currency units per month, so an implicit income must be added to the income of households that own their homes. The main difficulty is determining how to value the benefits that these families receive from their housing.

An attractive option might be to ask these families directly how much they think the housing is worth, by including a question such as “If this house were rented, what would be the estimated rent?” on a household survey. Indeed, many household surveys, such as the one used in this appendix, include such a question. However, this does not alleviate the problem for two reasons. First, households who own their homes often have poor information about housing markets (especially in poorer and more rural areas, and in less developed countries) and their answers to this type of question are often unreliable. This leads to measurement error, and because different types of households have varying degrees of information about housing markets, the measurement error is not uniform and is thus difficult to remedy. Second, many household surveys do not include such a question, so even if using this information was an acceptable solution, it is not viable in all countries. Another option is to use information from the subset of families that are renting their dwellings to estimate or predict the value that “owner-occupiers” receive from their housing. A relatively simple methodology used in some studies involves aggregating the total rent paid by households who rent their dwellings and dividing it by the total income of the same subset of households, which gives the proportion  $x$  of total income spent on rent by renters. The income of owner-occupiers is then divided by  $(1 - x)$  to add the imputed value of their housing. However, this methodology makes the unrealistic assumption that the value of housing is simply a constant proportion of income for all households. More realistically, the value of housing is likely a function of multiple factors, such as the characteristics of the dwelling. Another methodology is to regress the rent paid by renters on various dwelling characteristics, then use the coefficients from this regression to predict the value of housing for owner-occupiers.

The objective of this appendix is to test the latter methodology by fitting a linear model with monthly rent as the dependent variable, using the subset of households who rent their homes in a Brazilian household survey dataset. If a sufficiently good fit is achieved, this model can be used to predict housing value for owner-occupiers, which should provide more accurate information than the self-reported values. The appendix also seeks to provide a template for fitting such a linear model that can be modified and applied to other household survey datasets.

The appendix is divided into 4 sections, including this introduction. Section 2 describes the dataset, the relevant variables, and the data preparation and processing that took place prior to attempting to fit any models. Section 3 describes the model selection process. Section 4 summarizes the results, presents the main conclusions, and suggest direction for future research.

### Data

The analysis uses household survey micro-data from the 2008-2009 *Pesquisa de Orçamentos Familiares* (POF), an income-expenditure survey conducted approximately every five years by the Brazilian government's Institute of Geography and Statistics.<sup>38</sup> The sample size is 55,970 households and the sampling design is such that the survey is representative at the national level. The linear models used in this appendix restrict the analysis to the subset of households who rent their homes. Before dropping any observations (described below), this subset of the sample consists of 8,125 households.

The variable to be predicted by the linear model is monthly rent, and the potential independent variables related to the dwelling are the number of rooms in the dwelling, the number of bathrooms, the number of bedrooms, the type of dwelling (house, apartment, or single room in a shared building), the material of the walls, the material of the floors, whether the house has piped water, the source of the household's water, the dwelling's sewer or drainage system, the region in which the dwelling is located, the state in which the dwelling is located, and whether the dwelling is located in an urban or rural area. Because the objective of the model is to obtain a sufficiently good fit that can be used to predict the value that owner-occupiers receive from their housing rather than to simply predict real estate values, it also makes sense to include income as a potential variable, since this could be a good predictor of the amount families pay for their housing. Obviously, some of these variables in the above list will be highly collinear (by definition, the factor variables for state and region will be collinear, for example). Collinear variables will be eliminated before the model selection process, but all are considered as potential variables before selecting among them.

The first step is to look at the distribution of the dependent variable. Because the survey is conducted over a period of one year, monetary values are temporally deflated based on which part of the data collection period each household was interviewed; the temporally deflated values reflect real income and rent paid. This temporal deflation also solves the problem that people tend to pay rounded values in rent, so a table of non-deflated rent reveals high concentrations at values like 100 and 200 but low concentrations between them. An extreme values analysis shows that 34 renting households reported paying zero rent, and many more reported implausibly low values. Twelve reported values below one real (the exchange rate is approximately 2 reais = 1 US dollar),<sup>39</sup> and twelve more reported values below above 1 real but below 20 reais. The frequency of households reporting low rents increases around 20 reais per month, which is still low but possible for very low-quality housing in the less expensive regions of Brazil, so this is chosen as the cutoff for reasonable

---

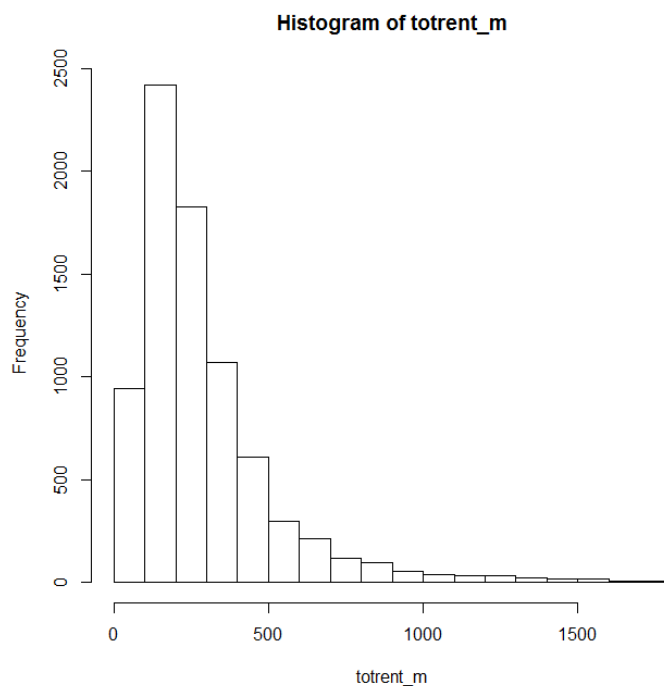
<sup>38</sup> This data set is available in non-delimited .txt format at [ftp://ftp.ibge.gov.br/Orçamentos\\_Familiares/Pesquisa\\_de\\_Orcamentos\\_Familiares\\_2008\\_2009/Microdados/Dados.zip](ftp://ftp.ibge.gov.br/Orçamentos_Familiares/Pesquisa_de_Orcamentos_Familiares_2008_2009/Microdados/Dados.zip)

<sup>39</sup> The Brazilian currency unit is called the real. The plural of real is reais. The nominal exchange rate as of December, 2011 was 1 US dollar = 1.85 reais. The purchasing power parity (PPP) adjusted exchange rate, based on the 2005 International Comparison Program (see World Bank, 2008), is \$1 PPP = 1.71 reais in 2009 prices (World Development Indicators, 2011).

values, and households reporting monthly rent below 20 reais are dropped from the dataset. After excluding all households reporting rents below 20 reais, the sample is 8,067 observations, or 99.2% of the original sample of renters. At the upper end, there is a long upper tail but no clear outliers or unreasonable values, so for now no additional observations are dropped.

Figure 1 is a histogram of monthly rent. Clearly, rents are very left-skewed. This suggests a transformation of the variable to achieve an approximately normal distribution. A Box-Cox transformation is considered, but because the value of  $\lambda$  is close to zero (and zero is in the 95% confidence interval for  $\lambda$ ), the more easily interpreted log transformation is chosen. After the transformation, the null hypothesis that the data is normally distributed is barely not rejected by the Shapiro-Francia test at a 5% significance level ( $p$ -value = 0.056). However, a more satisfactory distribution can be achieved if we do not consider the upper 1% of observations, who are not predicted well by the models anyway, as we will see later. In the final model, these observations are excluded, but they were included in some versions during the model selection process. With these observations excluded, the  $p$ -value of the Shapiro-Francia test is 0.209, the skewness is less than 0.001, and the kurtosis is 3.078.

**Figure C.1.** Histogram of monthly rent



Next, I consider household income. Because of the extensive questions about various income sources included in the household survey dataset, a number of definitions could be adopted for income, which must be constructed from the various income sources. This appendix uses monetary disposable income defined as follows: it includes labor income, non-labor income, private transfers, and government transfers, is net of direct taxes (but not net of employee contributions to social security which are considered a form of personal savings), and is calculated as the sum of all these

income sources from all members of the household, divided by the total number of members in the household. Alternative income definitions should have a negligible effect on the regression results.

There are quite a few households reporting zero income or with a missing value for income; these households were dropped from the dataset (while some households may have had legitimately zero income, only positive values can be considered for a Box-Cox or log transformation). Unreasonably low positive values were also dropped, again using 20 reais as the cutoff. In total, 155 observations, or 1.9% of the dataset, were dropped due to having zero or unreasonably low incomes. At the upper end, there is one clear outlier with monthly income of over 63,000 reais (with the next-highest observation having monthly income of 22,000 reais). This observation will clearly become a high leverage observation, but because it has the potential to be a “good” high leverage observation, it is not removed for the time being. Like rent, monthly income is highly left-skewed; a log transformation is chosen again and after the transformation the data is approximately normally distributed according to both the Shapiro-Francia test and an informal look at its skewness and kurtosis.

Moving on to dwelling characteristics, there are a few variables that describe the size of the house: total number of rooms, number of bedrooms, and number of bathrooms.<sup>40</sup> These should be highly correlated, and might also be correlated with other variables such as income; collinearity is addressed in Section 3. Since there are a limited number of responses to each of these questions, they can be treated as either a continuous or factor variable. Both options are considered in Section 3. Next, there are a number of descriptive factor variables. The material of the walls can be (i) brick; (ii) construction wood; (iii) mud; (iv) timber; (v) other.<sup>41</sup> The material of the roof can be (i) tile; (ii) concrete slab; (iii) construction wood; (iv) metal sheet; (v) timber; (vi) straw; (vii) other. The material of the floor can be (i) carpet; (ii) ceramic, tile, or stone; (iii) construction wood; (iv) cement; (v) timber; (vi) dirt; (vii) other. There is a binary variable for whether the dwelling has piped water in at least one room. The water source can be (i) a general distribution network; (ii) well or spring; (iii) other. The sewage or drainage system can be (i) sewage network; (ii) septic tank; (iii) cesspool; (iv) ditch; (v) river, lake, or ocean; (vi) other; (vii) none. There is a binary variable for whether the road is paved. The rent contract can be (i) verbal; (ii) documented by a real estate agency; (iii) documented by another source. Finally, there is a binary variable for urban vs. rural areas, and there are factor variables for the region (Brazil has five official geographic regions) and the state (there are 27 states including the federal district).

### *Model Selection*

Before fitting a model, this section begins by addressing collinearity between independent variables. There is obviously almost perfect correlation between Brazil’s states and its five official geographic

---

<sup>40</sup> A variable that is included in some datasets and would probably be helpful if it were included in this dataset is square footage.

<sup>41</sup> Straw is also an option for material of the walls, but there are no observations in my sample with straw walls.



regions, so only one of these variables can be used. Intuitively, since there are more states this should provide more information, so the region variable is eliminated from the list of potential independent variables. One would also expect the three variables related to the size of the house to have high correlation, and also to possibly be correlated with income.

Table 1 summarizes the pairwise correlations of number of rooms, number of bedrooms, number of bathrooms, and log income.

**Table C.1.** Pairwise correlations of rooms, bathrooms, bedrooms, and log income

	Rooms	Bathrooms	Bedrooms	Log Income
Rooms	1.00			
Bathrooms	0.66	1.00		
Bedrooms	0.52	0.29	1.00	
Log Income	0.25	0.31	-0.07	1.00

Surprisingly, log income is not very correlated with rooms, bathrooms, or bedrooms, which is good news for the model because it means there is no problem including both a size variable and log income as independent variables. The correlation between rooms and bathrooms, and that between rooms and bedrooms is high (as expected). We can also measure collinearity using tolerance; when regressing number of rooms on all other independent variables being considered in the model, the tolerance is 0.31, which is low enough to indicate that it should be excluded from the model. The tolerance from regressing number of bathrooms on all other independent variables except number of rooms is 0.76, indicating that there is not too much collinearity between bathrooms other independent variables. Similarly, the tolerance for bedrooms is 0.84. These results confirm the results from Table 1, and suggest that there are two options: either to include only rooms, or to exclude rooms and include both bathrooms and bedrooms. Based on looking at the correlations between these variables and log rent, and based on the formal comparison of a one-way ANOVA using rooms to a two-way ANOVA using bathrooms and bedrooms (I tested the latter with and without interaction, with very little difference between the two), I eliminate rooms from the list of potential variables but include both bathrooms and bedrooms.

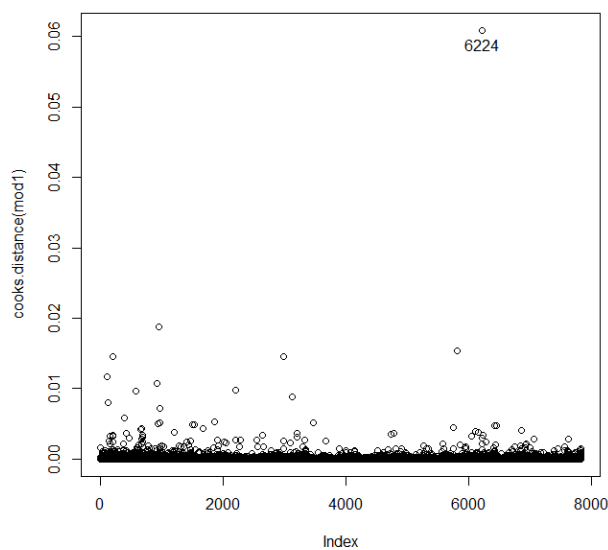
Further analysis of correlation and tolerance between all independent variables reveals that, unsurprisingly, the binary variable for whether the dwelling has piped water and the factor variable for the dwelling's water source are highly correlated; since the binary variable appears to be a better predictor of rent (based on correlation and a comparison of one-way ANOVA models), the factor variable is eliminated. The sewage variable is also correlated with whether the road is paved, and the sewage variable appears to be a better predictor of rent, so pavement is removed from the list of variables. The remaining variables exhibit sufficiently low collinearity. A final note on collinearity is that since factor variables are being used, with a dummy variable representing each possible value of the factor variable, one dummy variable must be removed from the regression for each factor variable (or, alternatively, the intercept term must be removed); otherwise there would be perfect

collinearity between the intercept and the group of dummy variables corresponding to each factor variable.

Now that the potential variables have been selected, I run a preliminary “full” model with all of these variables to look for other improvements. Initially I treat the number of bathrooms and bedrooms as continuous variables, but as mentioned before I will also test the model with them as factor variables. The output is voluminous because of all the factor variables, so it is omitted here, but will be presented for the final model. In the initial model, the signs on all of the variables make intuitive sense, and the adjusted  $R^2$  is 0.627.

Examining the studentized residuals, one observation has a leverage value (measured as its corresponding diagonal entry on the perpendicular projection operator [PPO] onto the column space of  $X$  [denoted  $C(X)$ ]) of nearly 1, but is well-predicted by the model; without the observation, the difference between that observation’s predicted value when it is included in the model and its predicted value when it is not included in the model is only 0.12, and its Cook’s Distance is 0.001. Thus, it is considered a “good” high-leverage value and is not dropped from the dataset. Even leverage values far from 1 can have a large impact on the model, so I also examine additional high leverage points with diagonal elements of the PPO onto  $C(X)$  significantly above the rest of the data points. One of these has a Cook’s Distance much higher than any other data point, as can be seen in Figure 2. Although it is still low (as expected in a large sample such as this one), with a value of 0.06, it is caused by the only household in the sample that had “other” material for both the walls and the roofing. Since this is a rarity, I chose to remove this observation, which improves the model’s adjusted  $R^2$  slightly.

**Figure C.2.** Cook’s Distance for full model



Other observations have lower Cook's Distances (all below 0.02); removing some observations with Cook's Distances in the 0.01 to 0.02 range improves the model's fit, but the improvement is modest (from an adjusted  $R^2$  of 0.628 with only the one observation removed to 0.631 with all eight observations with Cook's Distance greater than 0.01 removed). All of these observations correspond to observations with a unique combination of a couple factor variables, such as a straw roof and other material walls. The choice of whether to include these values ultimately comes down to the tradeoff between improved fit for the majority of observations at the expense of rare observations. Based on the objectives of this project, I choose to drop these observations, but the final results are fairly robust to the choice of keeping them in the dataset as well.

Returning briefly to the data point mentioned in Section 2 with monthly income of over 63,000 reais, where the next-highest household has monthly income of 22,000 reais, this data point turns out to cause no problems; it has a leverage value of 0.009 and a studentized residual of -0.17, indicating (given that it is a one-bedroom, one-bathroom house costing just 515 reais in monthly rent) that the dwelling characteristics were able to accurately predict this house's rent despite the outlier income. It is worth noting that *all* the observations with Cook's Distances above 0.01 were caused by rare combinations of dwelling characteristics, and all had income below the mean income of the sample, indicating that (contrary to my original hypothesis) abnormally high income does not lead to a poor prediction of rent paid.

To check whether the variables included in the model are all necessary, first the t-statistics of each coefficient can be examined. While some t-statistics indicate coefficients that are not statistically significant from zero, no continuous variable has a t-statistic significantly different from zero at the  $\alpha = 0.001$  significance level, and no factor variable has all the coefficients of its corresponding dummy variables statistically insignificant from zero, indicating that all of the factor variables add useful information to the model. Although the categories of some of the factor variables could be condensed based on high t-statistics, this does not coincide with the objective of this model of imputing rent to owner-occupiers. Likewise, a backward selection stepwise regression using the AIC criteria eliminates some categories of factor variables, but does not eliminate any continuous variables or all the categories of any factor variables (for any factor variable, it eliminates at most half of its categories).<sup>42</sup> Thus, in the interest of imputing rent to owner-occupiers, these dummy variables selected for deletion by the stepwise regression, which correspond to specific categories of factor variables (such as a few states and half of the possible categories for roofing material), are not eliminated from the model.

Finally, I compare the results from treating the bedrooms and bathrooms variables as continuous variables to treating them as factor variables. The range of bedrooms is 1-7 and the range of bathrooms is 0-6, indicating that they could be treated as factor variables. This option improves the adjusted  $R^2$  by less than 0.001, and again keeping the objective of this model in mind, it makes more

---

<sup>42</sup> It is worth noting that these eliminations would only improve the adjusted  $R^2$  by about 0.002.

sense to leave them as continuous variables because owner-occupiers may have a number of bedrooms or bathrooms that is outside the range of the subset of renters.

I also consider adding interaction terms. The main variables that might make sense to include an interaction term are the state factor variable and the urban/rural binary variable, since states might be heterogeneous. Including this interaction term improves the adjusted  $R^2$  by .003. As a side note, during earlier testing when I used regions instead of states, the interaction term between regions and rural areas was quite important. Since the interaction terms represent a modest improvement, the decision to exclude or include them is subjective. I would choose to include them in my final model, although in the interest of space I will present the results of the model without the interaction terms.

### *Results and Conclusions*

The results of the final model are presented in Table 2. As mentioned in Section 3, interaction terms between states and rural areas could be added, but in the interest of space they are not added here.

**Table C.2.** The final linear model

Dependent variable: log rent

Variable	Coefficient	Standard Error	t-value	P> t
(Intercept)	3.783947	0.09154	41.34	0
Bedrooms	0.138737	0.007252	19.13	0
Bathrooms	0.259012	0.011414	22.69	0
Log Income	0.171518	0.005832	29.41	0
Rural	-0.17687	0.023181	-7.63	0
States: Acre	-0.14086	0.064957	-2.17	0.03
Amazonas	-0.02609	0.054226	-0.48	0.63
Roraima	-0.01163	0.063199	-0.18	0.854
Pará	0.014309	0.050243	0.28	0.776
Amapá	0.198988	0.063449	3.14	0.002
Tocantins	-0.01976	0.051542	-0.38	0.702
Maranhão	-0.23796	0.049508	-4.81	0
Piauí	-0.50491	0.053528	-9.43	0
Ceará	-0.42792	0.048157	-8.89	0
Rio Grande do Norte	-0.22104	0.048911	-4.52	0
Paraíba	-0.48386	0.049537	-9.77	0
Pernambuco	-0.29827	0.045804	-6.51	0
Alagoas	-0.26159	0.044493	-5.88	0
Sergipe	-0.28956	0.047571	-6.09	0
Bahia	-0.34635	0.04684	-7.39	0
Minas Gerais	-0.24	0.043678	-5.49	0
Espírito Santo	-0.16072	0.044943	-3.58	0
Rio de Janeiro	-0.00601	0.047696	-0.13	0.9
São Paulo	-0.05234	0.044536	-1.18	0.24
Paraná	-0.11164	0.045599	-2.45	0.014
Santa Catarina	0.111191	0.047676	2.33	0.02
Rio Grande do Sul	-0.09296	0.049821	-1.87	0.062
Mato Grosso do Sul	-0.04044	0.044403	-0.91	0.362
Mato Grosso	0.052837	0.045502	1.16	0.246
Goiás	-0.02882	0.044443	-0.65	0.517
Distrito Federal	0.160134	0.050489	3.17	0.002
Apartment	0.165314	0.016825	9.83	0

Room in shared building	-0.12903	0.033176	-3.89	0
Walls: construction wood	-0.13986	0.023942	-5.84	0
Mud	-0.16778	0.117337	-1.43	0.153
Timber	-0.13436	0.095679	-1.4	0.16
Other	-0.06252	0.129957	-0.48	0.63
Sewage: septic tank	-0.12119	0.015311	-7.92	0
Cesspool	-0.17531	0.014548	-12.05	0
Ditch	-0.31991	0.044921	-7.12	0
River, lake, or ocean	-0.26252	0.03725	-7.05	0
Other	-0.19171	0.099212	-1.93	0.053
None	-0.05354	0.051671	-1.04	0.3
Piped water	0.271254	0.03304	8.21	0
Floor: Ceramic/tile/stone	-0.0196	0.063157	-0.31	0.756
Construction wood	-0.02479	0.065452	-0.38	0.705
Cement	-0.32295	0.064256	-5.03	0
Timber	0.037083	0.098852	0.38	0.708
Earth	-0.81236	0.180639	-4.5	0
Roofing: concrete	0.116321	0.014634	7.95	0
Construction wood	-0.03007	0.090701	-0.33	0.74
Metal sheet	-0.22445	0.081907	-2.74	0.006
Timber	0.157177	0.430246	0.37	0.715
Straw	-0.24537	0.174706	-1.4	0.16
Other	-0.03301	0.067885	-0.49	0.627
Contract: documented by a real estate agency	0.364923	0.016583	22.01	0
Docuemnted by another source	0.162513	0.012612	12.89	0

*Note:* omitted categories of factor variables are state: Rondônia; dwelling type: house; walls: brick; sewage: network; flooring: carpet; contract: verbal.

The adjusted  $R^2$  of the above regression is 0.631; with the interaction term between states and rural-urban it is 0.634. This is a reasonably good fit to predict the value of imputed rent for owner occupiers, and careful examination of the signs and magnitudes of the coefficients shows that they are all logical and reasonable. The main direction for future research is to use the model to impute the rent for owner-occupiers, and compare the self-reported housing values of owner-occupiers to the predicted values.

## References

- Abramovsky, Laura, Orazio Attanasio, and David Phillips. 2011. "A tax micro-simulator for Mexico (MEXTAX) and its application to the 2010 tax reforms." Institute for Fiscal Studies Working Paper.
- Adema, Willem and Maxime Ladaïque. 2005. "Net Social Expenditure, 2005 Edition: More Comprehensive Measures of Social Support." OECD Social, Employment and Migration Working Papers 29.
- Alleyne, Dillon, James Alm, Roy Bahl and Sally Wallace. 2004. "Tax Burden in Jamaica." Georgia State University International Studies Program Working Paper 04-34.
- Alm, James, Roy Bahl, and Matthew M. Murray. 1991. "Tax base erosion in developing countries." *Economic Development and Cultural Change* 39(4): 849-872.
- Angelucci, Manuela and Giacomo De Giorgi. 2009. "Indirect Effects of an Aid Program: How do Cash Transfers Affect Ineligibles' Consumption?" Working Paper 71. International Policy Center, Gerald R. Ford School of Public Policy, University of Michigan.
- Araar, Abdelkrim and Paolo Verme. "Reforming subsidies: a toolkit for policy simulations." World Bank Policy Research Working Paper 6148.
- Araar, Abdelkrim and Jean-Yves Duclos. 2012. "DASP: Distributive Analysis Stata Package. User Manual, DASP version 2.2." [http://dasp.ecn.ulaval.ca/modules/DASP\\_V2.2/DASP\\_MANUAL\\_V2.2.pdf](http://dasp.ecn.ulaval.ca/modules/DASP_V2.2/DASP_MANUAL_V2.2.pdf)
- Arze del Granado, Francisco, David Coady, and Robert Gillingham. "The unequal benefits of fuel subsidies: a review of evidence for developing countries." *World Development* 40(11): 2234-2248.
- Atkinson, Anthony B. 1980. "Horizontal Equity and the Distribution of the Tax Burden." in Aaron, H.J., Boskins, M.J. (eds), *The Economics of Taxation* (Washington D.C., Brookings), 3-18.
- \_\_\_\_\_. 1983. *Social Justice and Public Policy*. MIT Press.
- \_\_\_\_\_. 1987. "On the measurement of poverty." *Econometrica* 55(4), 749-764.
- Atkinson, Anthony B., Lee Rainwater, and Timothy M. Smeeding. 1995. Income distribution in OECD countries: Evidence from the Luxembourg Income Study (LIS). Social Policy Studies No. 18. Paris: Organization for Economic Cooperation and Development.
- Barr, Nicholas. 2004. *Economics of the Welfare State: Fourth Edition*. New York: Oxford University Press.
- Barrientos, Armando and Rachel Sabates-Wheeler. 2009. "Do Transfers Generate Local Economy Effects?" Working Paper 106. Brooks World Poverty Institute, University of Manchester.
- Barros, Ricardo, Francisco Ferreira, Jose Molinas Vegas and Jaime Saavedra Chanduvi. 2009. *Measuring Inequality of Opportunities in Latin America and the Caribbean*. Washington DC: World Bank. Available online <http://siteresources.worldbank.org/BRAZILEXTN/Resources/322340-1222953505624/BookHOI.pdf>
- Beckerman, Wilfred. 1979. "The impact of income maintenance payments on poverty in Britain, 1975." *Economic Journal* 89, 261-279.
- Bergh, Andreas. 2005. "On the counterfactual problem of welfare state research: How can we measure redistribution?" *European Sociological Review* 21(4).
- Birdsall, Nancy. 2010. "The (Indispensable) Middle Class in Developing Countries; or, The Rich and the Rest, Not the Poor and the Rest." In Ravi Kanbur and Michael Spence, eds., *Equity in a Globalizing World*. Washington, D.C.: World Bank.

- Birdsall, Nancy, Augusto de la Torre and Rachel Menezes. 2008. *Fair Growth: Economic Policies for Latin America's Poor and Middle-Income Majority*. Washington DC: Brookings Institution Press.
- Bourguignon, François and Luiz A. Pereira da Silva, eds. 2003. *The Impact of Economic Poverty and Income Distribution*. Washington DC: World Bank.
- Breceda, Karla, Jamele Rigolini and Jaime Saavedra. 2008. "Latin America and the Social Contract: Patterns of Social Spending and Taxation." Policy Research Working Paper 4604. World Bank Latin American and Caribbean Region Poverty Department Poverty Reduction and Economic Management Division. Washington DC: World Bank. Available online <http://go.worldbank.org/BWBRP91A50>
- Brewer, Mike and Cormac O'Dea. 2012. "Measuring living standards with income and consumption: evidence from the UK." Institute for Fiscal Studies Working Paper 12/12.
- Bucheli, Marisa, Nora Lustig, Maximo Rossi and Florencia Amabile. 2013. "Social Spending, Taxes and Income Redistribution in Uruguay." *Public Finance Review*, forthcoming.
- CEDLAS (Centro de Estudios Distributivos, Laborales y Sociales) and World Bank. 2012. "A Guide to the SEDLAC Socio-Economic Database for Latin America and the Caribbean." [http://sedlac.econo.unlp.edu.ar/download.php?file=archivos\\_upload\\_items\\_metodologia/Guide\\_14\\_english.pdf](http://sedlac.econo.unlp.edu.ar/download.php?file=archivos_upload_items_metodologia/Guide_14_english.pdf)
- Checchi, D. and Peragine, V. 2010. "Inequality of Opportunity in Italy." *Journal of Economic Inequality*, 8 (4), 429-450.
- Chen, Shaohua and Martin Ravallion. 2010. "The Developing World is Poorer than We Thought, but No Less Successful in the Fight Against Poverty." *The Quarterly Journal of Economics* 125(4): 1577-1625.
- Coady, David. 2006. "The distributional impacts of indirect tax and public pricing reforms", in A. Coudouel and S. Paternostro, eds., *Analyzing the Distributional Impact of Reforms: A Practitioner's Guide*. World Bank, Washington DC.
- Coady, David, Moataz El-Said, Robert Gillingham, Kangni Kpodar, Paulo Medas, and David Newhouse. 2006. "The Magnitude and Distribution of Fuel Subsidies: Evidence from Bolivia, Ghana, Jordan, Mali, and Sri Lanka." International Monetary Fund Working Paper 06/247.
- Cowell, F.A. and Flachaire, E. 2007. "Income distribution and inequality measurement: The problem of extreme values," *Journal of Econometrics*, 141(2), 1044–1072.
- Deaton, Angus. 2005. "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *The Review of Economics and Statistics* 87(1): 1-19.
- DeFina, Robert H. and Kishor Thanawala. 2004. "International evidence on the impact of transfers and taxes on alternative poverty indices." *Social Science Research* 33: 322-338.
- Dilnot Andrew, John Kay, and Michael Keen. 1990. "Allocating Taxes to Households: A Methodology." Oxford Working Papers 42(1): 210-230.
- Duclos, Jean-Yves. 2008. "Horizontal and Vertical Equity." *The New Palgrave Dictionary of Economics*. Eds. Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan.
- Duclos, Jean-Yves, Vincent Jalbert and Abdelkrim Araar. 2003. "Classical Horizontal Inequity and Reranking: An Integrating Approach." *Research and Economic Inequality* 10: 65-100.
- Duclos, Jean-Yves and Abdelkrim Araar. 2006. *Poverty and Equity: Measurement, Policy, and Estimation with DAD*. New York: Springer and International Development Research Centre.
- Duclos, Jean-Yves and Peter Lambert. 2000. "A normative approach to measuring classical horizontal inequity." *Canadian Journal of Economics* 33, 87-113.
- Economic Commission for Latin America and the Caribbean (ECLAC). 2010. Social Panorama of Latin America, 2009. Santiago, Chile: United Nations.

- Engel, Eduardo, Alexander Galetovi, and Claudio Raddatz. 1999. "Taxes and income distribution in Chile: some unpleasant redistributive arithmetic." *Journal of Development Economics* 59: 155-192.
- Ferreira, F.H.G., Gignoux, J. 2011. "The Measurement of Inequality of Opportunity: Theory and an Application to Latin America." *The Review of Income and Wealth*.
- Ferreira, Francisco, Julián Messina, Jamele Rigolini and Renos Vakis. 2013. *Socio-Economic Mobility and the Rise of the Middle Class in Latin America and the Caribbean*. World Bank Regional Flagship Report for Latin America and the Caribbean.
- Ferreira, Francisco H.G. and David Robalino. 2010. "Social Protection in Latin America: Achievements and Limitations." Policy Research Working Paper 5305. Washington DC: World Bank, Latin America and Caribbean Region Office of the Chief Economist, and Human Development Network Social Protection and Labor Unit. Available online [http://www-wds.worldbank.org/servlet/WDSCContentServer/WDSP/IB/2010/05/10/000158349\\_20100510134942/Rendered/PDF/WPS5305.pdf](http://www-wds.worldbank.org/servlet/WDSCContentServer/WDSP/IB/2010/05/10/000158349_20100510134942/Rendered/PDF/WPS5305.pdf)
- Fiszbein, Ariel, Norbert Schady, Francisco Ferreira, Margaret Grosh, Nial Kelleher, Pedro Olinto, and Emmanuel Skoufias. 2009. *Conditional Cash Transfers: Reducing Present and Future Poverty*. Washington DC: World Bank.
- Foster, James, Joel Greer, and Erik Thorbecke. 1984. "A class of decomposable poverty measures." *Econometrica* 52(3), 761-766.
- Foster, James and Anthony F. Shorrocks. "Poverty orderings." *Econometrica* 56(1), 173-177.
- Fullerton, Don and Diane Lim Rogers. 1991. "Lifetime versus annual perspectives on tax incidence." *National Tax Journal* 44(3): 277-287.
- Gallagher, Mark. 2005. "Benchmarking Tax Systems." *Public Administration and Development* 25: 125-144.
- Goñi, Edwin, J. Humberto López, and Luis Servén. 2011. "Fiscal Redistribution and Income Inequality in Latin America." *World Development* 39(9): 1558-1569.
- Grosh, Margaret, Carlo del Ninno, Emil Tesliuc, and Azedine Ouerghi. 2008. *For Protection and Promotion: The Design and Implementation of Effective Safety Nets*. Washington DC: World Bank. Available online [http://siteresources.worldbank.org/SAFETYNETSANDTRANSFERS/Resources/For\\_Protection\\_and\\_Promotion\\_complete.pdf](http://siteresources.worldbank.org/SAFETYNETSANDTRANSFERS/Resources/For_Protection_and_Promotion_complete.pdf)
- \_\_\_\_\_. 2012. "The Impact of Bolsa Família on Poverty: Does Brazil's Conditional Cash Transfer Program Have a Rural Bias?" *Journal of Politics and Society* 23: 88-125.
- Higgins, Sean and Nora Lustig. 2013. "Measuring Impoverishment: An Overlooked Dimension of Fiscal Incidence." Tulane University Department of Economics Working Paper 1315. <http://ideas.repec.org/p/tul/wpaper/1315.html>
- Higgins, Sean and Claudiney Pereira. 2013. "The Effects of Brazil's Taxation and Social Spending on the Distribution of Household Income." *Public Finance Review*, forthcoming.
- Hlasny, Vladimir and Paolo Verme. 2013. Top Incomes and the Measurement of Inequality in Egypt. World Bank Policy Research Working Papers No. 6557.
- Immervoll, Herwig, Horacio Levy, José Ricardo Nogueira, Cathal O'Donoghue, and Rozane Bezerra de Siqueira. 2009. "The Impact of Brazil's Tax-Benefit System on Inequality and Poverty." *Poverty, Inequality, and Policy in Latin America*. Eds. Stephan Klasen, and Felicitas Nowak-Lehmann. Cambridge: Mass.: MIT Press. 271-302.
- Jaramillo, Miguel. 2013. "The Incidence of Social Spending and Taxes in Peru." *Public Finance Review*, forthcoming.



- Jenkins, Stephen P., Richard V. Burkhauser, Shuaizhang Feng, and Jeff Larrimore. 2009. "Measuring inequality using censored data: a multiple-imputation approach to estimation and inference." *Journal of the Royal Statistical Society* 174 (1): 63-81.
- Kakwani, N.C. 1977. "Measurement of Tax Progressivity: An International Comparison." *The Economic Journal* 87(345): 71-80.
- \_\_\_\_\_. 1984. "On the measurement of tax progressivity and redistributive effect of taxes with applications to horizontal and vertical equity." *Advances in Econometrics* 3: 149-168.
- Korinek, A., Mistiaen, J.A. and Ravallion, M. (2006) Survey nonresponse and the distribution of income, *Journal of Economic Inequality*, 4, 33-55.
- Kharas, Homi. 2010. "The Emerging Middle Class in Developing Countries." OECD Development Centre Working Paper 285. Available online <http://www.oecd.org/dataoecd/12/52/44457738.pdf>
- Lambert, Peter. 1985. "On the redistributive effect of taxes and benefits." *Scottish Journal of Political Economy* 32(1): 39-54.
- \_\_\_\_\_. 2002. *The Distribution and Redistribution of Income: Third Edition*. Manchester United Kingdom: Manchester University Press.
- Lindert, Kathy, Emmanuel Skoufias, and Joseph Shapiro. 2006. "Redistributing Income to the Poor and Rich: Public Transfers in Latin America and the Caribbean." Social Protection Discussion Paper 0605. Washington, D.C.: The World Bank.
- Lora, Eduardo, ed. 2006. *The State of State Reforms in Latin America*. Washington DC: World Bank.
- Lopez-Calva, Luis F. and Ortiz-Juarez, Eduardo. 2013. "A Vulnerability Approach to the Definition of the Middle Class." *Journal of Economic Inequality*, forthcoming.
- Lopez-Calva, Luis F., Nora Lustig, John Scott, and Andres Castañeda. 2013. "Compromiso con la Equidad: Gasto Social, Desigualdad y Pobreza en México en 1996 y 2010." In press.
- Lustig, Nora, George Gray-Molina, Sean Higgins, Miguel Jaramillo, Wilson Jiménez, Veronica Paz, Claudiney Pereira, Carola Pessino, John Scott and Ernesto Yañez. 2012. "The Impact of Taxes and Social Spending on Inequality and Poverty in Argentina, Bolivia, Brazil, Mexico and Peru: A Synthesis of Results." Tulane University Economics Working Paper 1216, New Orleans, Louisiana, April 2012.
- Lustig, Nora, Carola Pessino, and John Scott. 2013. "The Impact of Taxes and Social Spending on Inequality and Poverty in Argentina, Bolivia, Brazil, Mexico and Peru: An Overview." *Public Finance Review*, forthcoming.
- Lusig, Nora and Carola Pessino. 2013. "Social Spending and Income Redistribution in Argentina During the 2000s: the Rising Role of Noncontributory Pensions." *Public Finance Review*, forthcoming.
- Lustig, Nora. 2000. "Crises and the Poor: Socially Responsible Macroeconomics." *Economía: The Journal of the Latin American and Caribbean Economic Association* 1(Fall): 1-45. Washington DC: Brookings Institution Press.
- Meyer, Bruce and James Sullivan. "Measuring the well-being of the poor using income and consumption." *Journal of Human Resources* 38: 1180-1220.
- Morra Imas, Linda G. and Ray C. Rist. 2009. *The Road to Results: Designing and Conducting Effective Development Evaluations*. Washington DC: World Bank.
- Murdoch, Jonathan. 1995. "Income Smoothing and Consumption Smoothing." *Journal of Economic Perspectives* 9(3): 103-144.
- O'Dea, Cormac and Ian Preston. 2012. "The distributional impact o public spending in the UK." IFS Working Paper 12/06.

- O'Donnell, Owen, Eddy van Doorslaer, Adam Wagstaff and Magnus Lindelow. 2008. "Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation." WBI Learning Resources Series. Washington, DC: The World Bank.
- Paz Arauco, Verónica, George Gray Molina, Wilson Jiménez Pozo, and Ernesto Yáñez Aguilar. 2013. "Explaining Low Redistributive Impact in Bolivia." *Public Finance Review*, forthcoming.
- Piketty, Thomas and Emmanuel Saez. 2007. "How Progressive is the U.S. Federal Tax System? A Historical and International Perspective." *Journal of Economic Perspectives* 21(1): 3-24.
- Plotnick, Robert. 1981. "A Measure of Horizontal Equity." *The Review of Economics and Statistics* 63(2), 283-288.
- Scott, John. 2011. "Gasto Público y Desarrollo Humano en México: Análisis de Incidencia y Equidad." Working Paper for *Informe sobre Desarrollo Humano México 2011*. Mexico City: UNDP.
- \_\_\_\_\_. 2013. "Redistributive Impact and Efficiency of Mexico's Fiscal System." *Public Finance Review*, forthcoming.
- Shah, Anwar, ed. 2003. *Handbook on Public Sector Performance Reviews*. Washington DC: The World Bank.
- Silveira, Fernando Gaiger, Jhonatan Ferreira, Joana Mostafa and José Aparecido Carlos Ribeiro. 2011. "Qual o Impacto da Tributação e dos Gastos Públicos Sociais na Distribuição de Renda do Brasil? Observando os Dois Lados da Moeda." *Progressividade da Tributação e Desoneração da Folha de Pagamentos Elementos para Reflexão*. Eds. José Aparecido Carlos Ribeiro, Álvaro Luchiezi Jr., and Sérgio Eduardo Arbulu Mendonça. Brasília: IPEA. 25-63.
- Slemrod, Joel. 1992. "Taxation and inequality: A time-exposure perspective." *Tax Policy and the Economy* 6: 105-127.
- Souza, Pedro H. G. F., Rafael G. Osorio, and Sergei Soares. 2011. "Uma metodologia para simular o Programa Bolsa Família." Instituto de Pesquisa Econômica Aplicada Working Paper, Brasília.
- Suits, Daniel B. 1997. "Measure of Tax Progressivity." *The American Economic Review* 67(4): 747-752.
- Urban, Ivica. 2009. "Kakwani decomposition of redistributive effect: Origins, critics and upgrades." ECINEQ Working Paper 2009-148.
- Urban, Ivica. 2013. "Implementation Issues in the Duclos-Jalber-Araar Decomposition of Redistributive Effect." *Public Finance Review* 41(1): 121-143.
- Van de Walle, Dominique and Kimberly Nead, eds. 1995. *Public Spending and the Poor: Theory and Evidence*. Baltimore and London: Published for the World Bank by John Hopkins University Press.
- Van Kerm, Philippe. 2009. "Income Mobility Profiles." *Economics Letters* 102(2): 93-95.
- World Bank. 2000/2001. "World Development Report 2000/2001: Attacking Poverty." Washington, DC and New York: Published for the World Bank by Oxford University Press.
- \_\_\_\_\_. 2006. "Country Policy and Institutional Assessments." *Operations Policy and Country Services*. Available online <http://siteresources.worldbank.org/IDA/Resources/CPIA2006Questionnaire.pdf>
- \_\_\_\_\_. 2009. "The World Bank's Country Policy and Institutional Assessment, An Evaluation." Independent Evaluation Group. Washington, DC: World Bank. Available online [http://siteresources.worldbank.org/EXTCPIA/Resources/cpia\\_full.pdf](http://siteresources.worldbank.org/EXTCPIA/Resources/cpia_full.pdf)
- \_\_\_\_\_. 2011. "CPIA Public Sector Management and Institutions Cluster Average." Available online <http://data.worldbank.org/indicator/IQ.CPA.PUBS.XQ>
- Yitzhaki, Schlomo and Edna Schechtman. 2013. *The Gini Methodology: A Primer on Statistical Methodology*. New York: Springer.



# WHAT IS CEQ?

Led by Nora Lustig (Tulane University) and Peter Hakim (Inter-American Dialogue), the Commitment to Equity (CEQ) project is designed to analyze the impact of taxes and social spending on inequality and poverty, and to provide a roadmap for governments, multilateral institutions, and nongovernmental organizations in their efforts to build more equitable societies. CEQ/Latin America is a joint project of the Inter-American Dialogue (IAD) and Tulane University's Center for Inter-American Policy and Research (CIPR) and Department of Economics. The project has received financial support from the Canadian International Development Agency (CIDA), the Development Bank of Latin America (CAF), the General Electric Foundation, the Inter-American Development Bank (IADB), the International Fund for Agricultural Development (IFAD), the Norwegian Ministry of Foreign Affairs, the United Nations Development Programme's Regional Bureau for Latin America and the Caribbean (UNDP/RBLAC), and the World Bank. <http://commitmenttoequity.org>



**COMMITMENT  
TO EQUITY**

The CEQ logo is a stylized graphical representation of a Lorenz curve for a fairly unequal distribution of income (the bottom part of the C, below the diagonal) and a concentration curve for a very progressive transfer (the top part of the C).