

# Health Equity and Financial Protection

Adam Wagstaff  
Marcel Bilger  
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THE WORLD BANK



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STREAMLINED ANALYSIS WITH ADePT SOFTWARE

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**THE WORLD BANK**  
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# Foreword

World Bank researchers have a long tradition of developing and applying methods for the analysis of poverty and inequality, often working with collaborators. And the Bank's researchers have often tried hard to make their methods accessible to others, through "how-to" guides and training courses.

In that tradition, this book is the first in a new series called Streamlined Analysis with ADePT Software. ADePT is an exciting new software tool developed by the Bank's research department, the Development Research Group. ADePT automates the production of standardized tables and charts using a wide range of methods in distributional analysis, including some advanced methods that are technically demanding and not easily accessible to most potential users. This software makes these sophisticated methods accessible to analysts who have limited programming skills. (ADePT uses the statistical software package Stata but does not require that users know how to program in Stata, or even to have Stata installed on their computers.) But we also hope that ADePT will be valuable to more technically inclined researchers too, by speeding up the production of results and by increasing their reliability and comparability.

The present book provides a guide to ADePT's two health modules: the first module covers inequality and equity in health, health care utilization, and subsidy incidence; the second, health financing and financial

## Foreword

protection. It also provides introductions to the methods used by ADePT and a step-by-step guide to their implementation in the program.

We hope you find this guide useful in your work. Please give us feedback on ADePT (see [www.worldbank.org/adept](http://www.worldbank.org/adept)) and this volume, as we wish to make them even more useful in the future.

*Martin Ravallion*  
Director, Development Research Group  
The World Bank

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# Abbreviations

ADePT	Automated DEC Poverty Tables
BIA	benefit incidence analysis
BMI	body mass index
CHC	commune health center
CPI	consumer price index
DEC	Development Economics (Vice Presidency at the World Bank)
ID	identification
NHA	National Health Account
OLS	ordinary least squares
OOP	out of pocket
PPP	purchasing power parity
VHLSS	Vietnam Household Living Standards Survey



# Introduction

ADePT is a software package that generates standardized tables and charts summarizing the results of distributional analyses of household survey data. Users input a Stata (or SPSS) data set, indicate which variables are which, and tell ADePT what tables and charts to produce; ADePT then outputs the results in a spreadsheet with one page for each requested table and chart. ADePT requires only limited knowledge of Stata and SPSS: users need to be able to prepare the data set, but do not need to know how to program Stata to undertake the often complex analysis that ADePT performs. ADePT frees up resources for data preparation, interpretation of results, and thinking about the policy implications of results. Users can easily assess the sensitivity of their results to the choice of assumptions and can replicate previous results in a straightforward way. ADePT also reduces the risk of programming errors and spurious variations in results that arise as a result of different ways of implementing methods computationally.

ADePT Health is just one of several modules; other modules include Poverty, Inequality, Labor, Social Protection, and Gender. ADePT Health has two submodules: Health Outcomes and Health Financing. Together these modules cover a wealth of topics in the areas of health equity and financial protection.

This manual is divided into two parts corresponding to each of these submodules. The following topics are covered:

- *Part 1, Health Outcomes:* (a) measuring inequalities in outcomes and utilization (with and without standardization for need), (b) decomposing the causes of health sector inequalities, and (c) analyzing

the incidence of government spending (that is, benefit incidence analysis).

- *Part 2, Health Financing*: (a) financial protection, including catastrophic payments and impoverishing payments, and (b) the progressivity and redistributive effect of health financing.

Each part is divided into six chapters:

- Chapters 2 and 8 explain what ADePT does in each area and provide a brief introduction to the methods underlying ADePT. The methods are widely accepted in the literature and are outlined in more detail in *Analyzing Health Equity Using Household Survey Data*, by Owen O'Donnell, Eddy van Doorslaer, Adam Wagstaff, and Magnus Lindelow (O'Donnell and others 2008). This first section and all the other sections of this manual draw heavily on this book.
- Chapters 3 and 9 explain how to prepare the data for ADePT. This is key to the successful use of ADePT, as the software has no data manipulation capability.
- Chapters 4 and 10 guide users through example data sets, which are used in the worked examples in the sections that follow.
- Chapters 5 and 11 show users how to generate the tables and charts that ADePT is capable of producing. Using a worked example with real data, the manual provides step-by-step instructions for using ADePT.
- Chapters 6 and 12 walk users through interpretation of the tables and charts produced by ADePT. Again, this is done through a worked example using real data.
- Chapters 7 and 13 contain technical notes explaining in more detail the methods used in the program.

## Reference

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O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow. 2008. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.



# **PART I**

## **Health Outcomes, Utilization, and Benefit Incidence Analysis**



# What the ADePT Health Outcomes Module Does

The Health Outcomes module of ADePT Health allows users to analyze inequalities in health, health care utilization, and health subsidies, by income or any continuous (though not necessarily cardinal) measure of living standards or socioeconomic status. In what follows, “income” is often used as shorthand for whatever measure of living standards is being used. ADePT allows analysts to see whether inequalities, in, for example, the use of health care between the poor and rich, have narrowed over time or are smaller in one country than another. Users can also analyze whether (and how far) subsidies to the health sector disproportionately benefit the better off or the poor—that is, benefit incidence analysis, or BIA.

ADePT can do quite simple analysis as well as more sophisticated analysis. The more sophisticated features of ADePT are indicated below with an asterisk. Users not familiar with the literature may wish to focus initially on the sections without an asterisk. Except where stated, the summary in this chapter relies on O'Donnell and others (2008).

## Measuring Inequality in Outcomes and Utilization

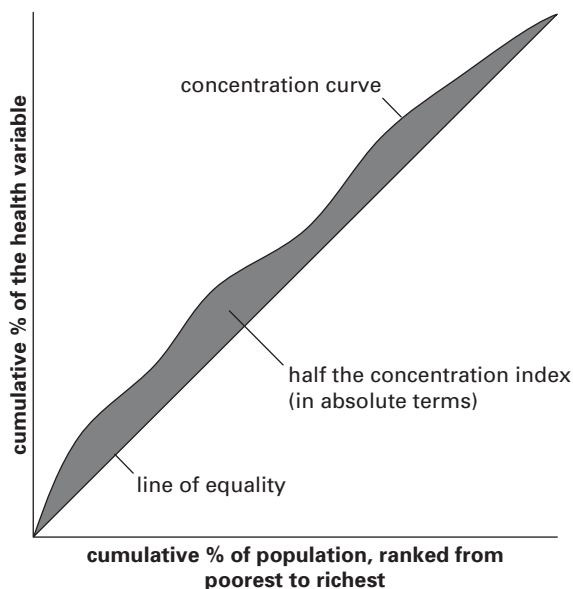
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ADePT allows users to analyze differences in health outcomes or health care utilization across any subpopulation. However, the software's strength lies in its ability to analyze inequalities in health outcomes and utilization by *income* or by some other measure of living standards.

## Basic Inequality Analysis

In addition to producing tables showing the mean values by income group (or any grouping of living standards), ADePT produces a summary inequality statistic, known as the *concentration index*, which shows the size of inequalities in health and health care utilization between the poor and better off (see figure 2.1).<sup>1</sup> A large absolute value indicates a high degree of inequality. The concentration index derives from the *concentration curve*, which is graphed by ADePT. It is obtained by ranking individuals by a measure of living standards and plotting on the x axis the cumulative percentage of individuals ranked in ascending order of standards of living and on the y axis the cumulative percentage of total health care utilization, health or ill health, or whatever variable whose distribution is being investigated. The y axis could measure, for example, the percentage of people reporting an inpatient episode. This exercise traces out the concentration curve. If hospital admissions are not related to living standards, the concentration curve will be a straight line running from the bottom left corner to the top right corner; this is the line of equality. If the better off have

**Figure 2.1: Concentration Curve and Index**



Source: Authors.

higher inpatient admission rates than the poor, the concentration curve will lie below the line of equality. It will lie above the line of equality in the opposite case.

Twice the area between the concentration curve and the line of equality is the concentration index. By convention, it is positive when the concentration curve lies below the line of equality, indicating that the variable of interest is lower among the poor and has a maximum value of +1. It is negative when the concentration curve lies above the line of equality, indicating that the outcome variable is higher among the poor and has a minimum value of -1.

### **Standardization for Demographic Factors\***

ADePT allows users to request that inequalities in health and utilization be adjusted to reflect differences across income groups in variables that are justified determinants of health or utilization.<sup>2</sup> Utilization might be higher among the poor, for example, in part because the poor have greater medical needs, and greater medical needs translate, as policy makers hope they do, into higher levels of utilization; standardization provides a way to remove this justified inequality from the measured inequality. Similarly, health may be worse among the poor because the poor are, on average, older than the better off, and people's health inevitably worsens with age; standardization provides a way to remove this inescapable component of health inequality.<sup>3</sup>

ADePT implements both the direct and indirect methods of standardization and allows users to decide whether to include only justified influences in the standardization or both justified *and* unjustified influences, albeit standardizing just for the former. Best practice is to include both sets of variables.<sup>4</sup>

### **Accounting for Inequality Aversion\***

The concentration index embodies a specific set of attitudes toward inequality.<sup>5</sup> ADePT reports values of a generalized or "extended" concentration index with different values of an inequality-aversion parameter. The higher the value of the parameter, the greater is the degree of aversion to inequality. The normal concentration index has a value of 2 for the inequality-aversion parameter.

### Trading Off the Average against Inequality\*

Policy makers are typically concerned not just about health sector inequalities but also about the *level* of the variable in question.<sup>6</sup> Obviously, they would like both low inequality and better health. But at the margin they are likely to be willing to trade off one against the other, accepting a little more inequality in exchange for a dramatic improvement in the average. ADePT reports values of the health achievement index that trade off average health against inequality. Specifically, it is equal to the mean of the distribution multiplied by the complement of the concentration index. It therefore reflects the average of the distribution and the concentration index. If there is no inequality, so that the concentration index is 0, the achievement index is equal to the average. If outcomes are concentrated among the poor, so that the concentration index is negative, the achievement index exceeds the average. For example, if child mortality is higher among the poor, “achievement” (in this case dis-achievement!) is higher than average child mortality.

ADePT also reports values of an “extended” achievement index, corresponding to the extended concentration index.

### Explaining Inequalities and Measuring Inequity\*

---

In addition to *measuring* inequalities in health and health care utilization across the income distribution, ADePT can also be used to *explain* inequalities in terms of inequalities in the underlying determinants.<sup>7</sup> For example, part of the observed pro-poor inequality in utilization might be because the elderly are, on average, worse off than the nonelderly and use more services. Part of it might be due to the fact that insurance is higher among the better off and the insured use more services. ADePT allows users to see how far utilization inequalities are due to the concentration of the elderly among the better off rather than to the concentration of the insured among the better off. ADePT allows any number of determinants of utilization (or health) to be included and calculates the portion of inequality that is due to inequality in each determinant.

Here’s how the decomposition works. Suppose the variable of interest can be expressed as a linear function of a set of determinants. Then the concentration index of the variable of interest is a linear function of the concentration indexes of the determinants, where the weight on each determinant is equal to

the regression coefficient of the determinant in the regression of the variable of interest on the full set of determinants, times the mean of the determinant, divided by the mean of the variable of interest. So the bigger the effect of the determinant on the variable of interest, the bigger the mean of the determinant, and the more unequally distributed the determinant, the more the (inequality in the) determinant contributes to the inequality in the variable of interest. ADePT reports how much of the inequality in the variable of interest can be attributed to inequalities in each of the determinants.

There is a link between the decomposition approach, the measurement of inequity, and the indirect standardization. Suppose we divide the determinants into (a) justified influences on the variable of interest (for example, health if the outcome of interest is utilization) and (b) unjustified determinants (for example, insurance). It turns out that the concentration index minus the combined contribution in the decomposition of the standardizing variables is equal to the concentration index for the indirectly standardized values of the variable of interest. And, in the case of utilization, the difference between the concentration index for utilization and the concentration index for the indirectly standardized values of utilization is equal to one of the two widely used indexes of inequity, that is, a measure of the amount of unjustified inequality. So, in a single sweep, the decomposition provides a way not just of *explaining* inequality but also of *measuring* inequity. Actually, the decomposition approach gives analysts a good deal of flexibility in choosing what to include among the justified determinants and what to include among the unjustified determinants. For example, people get less healthy as they age, suggesting that age might be a justified influence in an analysis of health inequalities. However, the speed at which people's health deteriorates as they age is not fixed and can be affected by policy makers. Perhaps, therefore, it ought not to be viewed as a justified or inescapable influence on health in an analysis of the causes of health inequality. The attractive feature of the decomposition is that analysts can "sit on the fence" completely and simply report the contributions to inequality coming from each of the determinants, letting readers decide where to draw the line.

### **Benefit Incidence Analysis**

---

The final type of analysis that the Health Outcomes module of ADePT allows users to undertake is benefit incidence analysis.<sup>8</sup> This involves

analyzing the distribution of government health sector subsidies across the income distribution.<sup>9</sup>

## Basic BIA

The problem facing analysts undertaking a BIA is that the amount the government spends providing care to a specific individual is not observed, and therefore assumptions have to be made to derive subsidies at the household level.<sup>10</sup> The least demanding assumption—in terms of data—is that unit subsidies are constant. In this case, as table 2.1 shows, the analyst simply requires data on utilization of different types of public sector health care providers (for example, health centers, outpatient care in hospitals, and inpatient care in hospitals) and the amount the government spends on each type of service. By grossing up the average amounts of utilization to the population level, ADePT estimates the total volume of utilization for each type of service. This is divided into the amount the government spends on each type of service to get the unit subsidy for each type of service. This is then assumed to be constant within a given type of service.

**Table 2.1: Data Needed for Different Types of ADePT Health Outcome Analysis**

<i>Topic and analysis</i>	<i>Living standards indicator</i>	<i>Health outcome variable(s)</i>	<i>Demographic variables and other health determinants</i>	<i>Health utilization variable(s)</i>	<i>Need indicators and other utilization determinants</i>	<i>National Health Account data on subsidies</i>	<i>Fees paid to public providers</i>
<i>Inequalities in health</i>							
No standardization	✓	✓					
Standardization and decomposition*	✓	✓	✓				
<i>Inequalities in utilization</i>							
No standardization	✓			✓			
Standardization and decomposition*	✓			✓	✓		
<i>Benefit incidence analysis</i>							
Constant unit subsidy assumption	✓			✓		✓	
Other assumptions*	✓			✓		✓	✓

Source: Authors.

Note: \* = A more advanced and more data-demanding type of analysis.



### **BIA under Alternative Assumptions\***

Other assumptions also require data on the amount that different households (or individuals) pay in fees for the visits to public sector providers that are recorded in the household data. The other assumptions are that unit costs are constant and proportional to the fees paid. If data are available on fees paid to public providers, ADePT reports BIA estimates for these cases too.

ADePT reports the average subsidy (by type of service and for all services combined) for each quintile or decile. It produces separate tables for each assumption. ADePT also reports the concentration index inequality statistic showing, on balance, how pro-poor or pro-rich subsidies are and graphs subsidy concentration curves for different categories of utilization.

### **Notes**

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1. For further details, see technical notes 1–3 in chapter 7; O'Donnell and others (2008, chs. 7, 8).
2. For further details, see technical note 6 in chapter 7; O'Donnell and others (2008, 60–64).
3. See Gravelle (2003) and Fleurbaey and Schokkaert (2009) for discussions on which sources of inequality in health and health care utilization should be considered justified or fair.
4. See, for example, Gravelle (2003); van Doorslaer, Koolman, and Jones (2004); Fleurbaey and Schokkaert (2009).
5. For further details, see technical note 4 in chapter 7; O'Donnell and others (2008, ch. 9).
6. For further details, see technical note 5 in chapter 7; O'Donnell and others (2008, ch. 9).
7. For further details, see technical notes 6 and 7 in chapter 7; O'Donnell and others (2008, chs. 13, 15).
8. For further details, see technical notes 9–11 in chapter 7; O'Donnell and others (2008, ch. 14); Wagstaff (2010).
9. For further details on BIA, see technical notes 9–11 in chapter 13; O'Donnell and others (2008, ch. 14); Wagstaff (2010). For a critique of BIA, see van de Walle (1998). Empirical studies include Hammer, Nabi, and Cercone (1995); van de Walle (1995); O'Donnell and others

(2007). Marginal BIA tries to assess how different income groups benefit from an *expansion* of the budget (Lanjouw and Ravallion 1999). A pro-rich distribution of *average* benefits need not translate into a pro-rich distribution of *marginal* benefits, since additional spending may disproportionately benefit the poor rather than the rich. ADePT does not currently implement marginal BIA. However, analysts can easily repeat the same BIA on data sets from multiple years or regions within the country and see how incidence changes as budgets change.

10. Wagstaff (2010) extends the analysis in O'Donnell and others (2008).

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# Data Preparation

ADePT has no data manipulation capability. Hence, the data need to be prepared *before* they are loaded into ADePT. This chapter outlines the data needed by ADePT for different types of analysis.

The data required for the various analyses that ADePT can do are summarized in table 2.1. An alternative way of reading the table is to see what analyses are feasible given the available data. ADePT works out what tables and graphs can be produced *given the data fields completed*: tables and graphs that are feasible are shown in black; those that are not feasible are shown in gray. As the level of sophistication of the analysis increases, so do the data requirements. The more sophisticated analyses—hence more demanding of data—are marked with an asterisk in table 2.1.

## Household Identifier

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ADePT users must specify a household identification variable, or series of variables, that uniquely identifies the household in the data set.

## Living Standards Indicators

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ADePT analyzes the distribution of health outcomes, health care utilization, or subsidies *across people with different standards of living*. As table 2.1 shows, *all* ADePT tables and charts require a living standards measure.

This raises the question of how to measure living standards. One approach is to use “direct” measures, such as income, expenditure, or consumption. The alternative is to use an indirect or “proxy” measure, making the best use of available data.

### **Direct Approaches to Measuring Living Standards**

The most direct (and popular) measures of living standards are income and consumption. Income refers to the earnings from productive activities and current transfers. It comprises claims on goods and services by individuals or households. In other words, income permits people to obtain goods and services.

Consumption, by contrast, refers to resources actually consumed. Although many components of consumption are measured by looking at expenditures, there are important differences between consumption and expenditure. First, expenditure excludes consumption that is not based on market transactions. Given the importance of home production in many developing countries, this can be an important distinction. Second, expenditure refers to the purchase of a particular good or service. However, the good or service may not be immediately consumed, or at least it may have lasting benefits. This is the case, for example, with consumer durables. Ideally, in this case, consumption should capture the benefits that come from the *use* of the good, rather than the value of the purchase itself.

There is a long-standing and vigorous debate about which is the better measure of standards of living—consumption or income. *For developing countries, a strong case can be made for preferring consumption over income, based on both conceptual and practical considerations.* Measured income often diverges substantially from measured consumption, in part due to conceptual differences between them—it is possible to save from income and to finance consumption from borrowing. Income data are, moreover, often of poor quality, if available at all.

If consumption data are used as a measure of living standards, it is customary to divide total household consumption (or income) by the number of household members (or the number of *equivalent* household members) to get a more accurate measure of the household’s standard of living. The per capita adjustment is quite common in empirical work in this area.

## Indirect Approaches to Measuring Living Standards

Many surveys do not include data on either income or consumption. Sometimes, consumption data are available, but they are not very high quality. In such situations, a popular strategy is to use principal components analysis (or some other statistical method) to construct an index of “wealth” from information on household ownership of durable goods and housing characteristics. This provides a *ranking variable*. In other words, it is possible to say whether a household is wealthier than another household, but not *how much* wealthier. For the analyses done by the Health Outcomes module of ADePT, this is not a limitation. (It is a limitation in the Health Financing module.) Finally, because a wealth index is not a cardinal measure of living standards, ADePT users should *not* try to adjust the wealth index for household size.

## Health Outcome Variables

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A variety of health outcome variables can be used in ADePT to analyze inequalities in health.<sup>1</sup> These can be grouped under (a) child survival, (b) anthropometric indicators (which apply to both children and adults), and (c) other measures of adult health.

### Child Survival

ADePT can be used to analyze inequalities in infant- and under-five mortality by creating a dummy variable taking a value of 1 if the child died before his or her first (or fifth) birthday.<sup>2</sup> To get around the censoring problem (that is, some children who have not yet reached their first birthday might never do so), ADePT users might want to drop from the sample children who have not yet reached their first (or fifth) birthday. ADePT can also *explain* inequalities in child survival using the decomposition method. The basic output in the ADePT decomposition is based on the use of a standard ordinary least squares (OLS) regression model. However, ADePT will detect if the outcome variable is binary (for example, whether the child has died) and will produce a second set of output based on the results from a probit model and a linear approximation of the decomposition with marginal effects evaluated at sample means.<sup>3</sup>

## Anthropometric Indicators

Anthropometric indicators capture malnutrition.<sup>4</sup> Raw anthropometric data on weight, age, and so forth can be turned into more meaningful indicators by standardizing them on a reference population. Common referenced variables include weight-for-age, height-for-age, underweight, body mass index (BMI), and mid-upper arm circumference. The raw data need to be converted *before* the data are loaded into ADePT: this can be done in Stata using the `zanthro` command.

Anthropometric indicators are sometimes dummy variables, such as underweight or not. Sometimes they are continuous variables, such as weight-for-age, which is a  $z$  score, or the child's percentile in the reference distribution. Both dummy and continuous variables can be used in ADePT to measure malnutrition inequalities and to decompose the causes of inequality. Continuous variables such as weight-for-age and BMI lend themselves naturally to linear decomposition. Inequalities in dummy variables (such as underweight) can also be decomposed. The initial output from ADePT is based on a standard OLS model, but ADePT detects whether the outcome variable is a binary variable and produces a second set of results based on the output of a probit model and a linear approximation of the decomposition with marginal effects evaluated at sample means.

## Other Measures of Adult Health

The measurement of adult health is more complex than the measurement of child survival and the measurement of malnutrition. Adult health measures differ along several dimensions. One is whether the health data are self-perceived (the occurrence of an illness during a specific time period) or observed (blood pressure). Another is whether a measure reflects a medical concept of health (the presence of a chronic condition), a functional concept (impairment in ability to perform everyday activities), or a subjective concept (answers to the question, how do you rate your health?). Health variables also vary in terms of *how they are measured*. Some are continuous variables (the number of days off work during the past four weeks), some are binary variables (the presence of chronic illness), and some are multiple-category variables. The last cannot simply be scored 1, 2, 3, and so forth because the true scale will not necessarily be equidistant between categories. O'Donnell and others (2008) review various options for



multiple-category variables. Typically these require ADePT users to assign values to the categories using one of the suggested options *before* loading the data into ADePT.

Three points not made in O'Donnell and others (2008) are also worth making:

- There has been some debate in the recent literature about whether measures of health inequality like the concentration index need “correcting” when the variable in question is bounded, not cardinal, or both.<sup>5</sup> Currently, ADePT does not offer any correction. However, all corrections proposed in the literature can be made *ex post* in the ADePT Excel output file.
- There has been some discussion about whether measures of inequalities in self-perceived health status are biased because the poor and better off have different cutoff points between categories of health status. For instance, at equal latent (that is, unobservable) health status, the poor might report being in very good health, whereas the better off might report being in only fair health. One approach is to anchor the cutoff points using responses to anchoring vignettes in which everyone is asked to rate the health of a hypothetical individual with specific health problems; the results (for three developing countries) do not suggest that inequalities are much affected by reporting bias.<sup>6</sup> ADePT does not allow such an adjustment to be undertaken in the program; however, users could apply the vignette anchoring methodology beforehand and load into ADePT the predicted latent health scores adjusted for shifts in cutoff points.
- Finally, many measures of health status capture ill health over a specific period of time. For example, a classic question asks whether people were ill during the previous month. There is some evidence that the recall period chosen has differential effects on reporting by the poor and rich. A recent study finds a steeper income gradient in self-reported illness when a weekly recall period is used than when a monthly recall period is used.<sup>7</sup> The authors argue that the poor forget illness that becomes accepted as part of their normal life. As they put it, “Poor people are ill for large fractions of the year with ailments that are short term and, apparently, easily forgotten. Richer people, who do not forget as easily, do not suffer from acute illnesses nearly as much as the poor.” This has implications for the

choice of recall period when designing a survey and for the interpretation of results when using a survey with a longer recall period.

### Health Utilization Variables

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Health care utilization variables are required for an analysis of inequalities and inequities in health care utilization, but also for a benefit incidence analysis (BIA). Health utilization is generally easier to measure than health status, at least on the face of it. Common examples are whether or not someone used a particular type of provider during the previous month, the number of outpatient consultations during the past month, and the number of inpatient days over the previous year. Two aspects of such variables are worth noting:

- The first is that these variables—like other commonly used utilization measures—are either binary or count variables. With binary variables, the issues concerning the desirability of “correcting” the concentration index are worth keeping in mind. Issues also arise in the decomposition exercise. The basic decomposition tables that ADePT produces are based on a standard OLS regression. However, ADePT checks whether the utilization measure is a binary or a count variable and, if so, also reports a further set of decomposition results based on a probit or Poisson model as appropriate, using a linear approximation of the decomposition with partial effects evaluated at the sample means.<sup>8</sup>
- The second point worth making is that utilization is always measured over a specific period of time. As with the reporting of ill health, there is some evidence that the recall period differentially affects reporting by the poor and rich, with doctor visits declining with income when measured using a weekly recall period but *increasing* with income when using a monthly recall period.<sup>9</sup> This has implications for the choice of recall period when designing a survey and for the interpretation of results when using a survey with a longer recall period.

When ADePT users undertake a BIA, the measures of utilization should cover the utilization of different types of public facilities (and private facilities

if they are subsidized through supply-side subsidies). Examples of obvious variables are the number of outpatient visits at health centers, the number of outpatient visits at hospitals, and the number of inpatient admissions.

## **Variables for Basic Tabulations**

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Optionally, users can specify variables beyond the living standards variable by which ADePT should tabulate health outcomes or utilization. These can be individual-level variables (age, gender, education, employment status, and an additional variable chosen from the data set) or household-level variables (urban, region, and an additional variable selected from the data set). ADePT tabulates mean values of health or utilization by categories of whichever variables are selected.

## **Weights and Survey Settings**

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If appropriate, weights should be specified that make the results representative at the population level. This should be the household weight. ADePT will automatically multiply it by household size to make the figures representative at the population level.

## **Determinants of Health**

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Demographic variables and other health determinants are required if ADePT users want to standardize inequalities in health for demographic differences across quintiles of the living standards variable or to decompose inequalities in health into their causes.<sup>10</sup>

The demographic variables that are typically used in these analyses are age and gender. These are required for any standardization and decomposition analysis.

Other health determinants are also required for standardization and decomposition. Which other health determinants (or control variables) are included will vary according to the application, but as many as possible should be included, especially those that are likely to be correlated with demographic variables. ADePT users will likely want to include at a

minimum the living standards indicator among these variables. It could be included as a single variable or as a vector of variables capturing quintiles of the living standards indicator. (This quintile variable needs to be constructed before the data are loaded into ADePT.) Education (of the mother and possibly of the father too) is a common variable to include among determinants of child health; other obvious candidates include access to safe water and hygienic sanitation. ADePT users would do well to consult the previous literature on the determinants of the health outcome indicator(s) whose inequality is being analyzed.

### Determinants of Utilization

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Indicators of need and other determinants of utilization are required (a) if the goal is to standardize inequalities in utilization for differences in need across quintiles so as to estimate *inequity* or (b) if the goal is to decompose inequalities in utilization into their causes.<sup>11</sup>

The usual indicators of need include demographic variables (age and gender) and measures of health status. These are required for any standardization and decomposition analysis.

Other (non-need) determinants of utilization are also required for standardization and decomposition. Which non-need determinants (or control variables) are included will vary according to the application, but as many as possible should be included, especially those that are likely to be correlated with need variables. ADePT users will likely want to include at a minimum the living standards indicator, either as a single variable or as a vector of variables capturing quintiles of the living standards indicator. (This quintile variable needs to be constructed before the data are loaded into ADePT.) Other candidates for non-need determinants of utilization include insurance status and distance to the closest health facility, among others.

### Information on Utilization for Benefit Incidence Analysis

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A BIA requires information from the household survey on the quantities used of different types of services, for example, ambulatory visits to a first-level provider, ambulatory visits to a hospital, inpatient admissions to a hospital, and so forth. These should all refer to the same time period.

## Fees Paid to Public Providers

A BIA that does not rest exclusively on the assumption of a constant unit subsidy requires survey data on the amounts that patients pay to government health facilities. Ideally, this would be available by type of service, such as the amount paid out-of-pocket for each ambulatory visit to a first-level provider. ADePT is, however, able to handle the case where only total out-of-pocket payments to *all* public facilities combined are recorded. ADePT always assumes that the out-of-pocket payments recorded in the survey are accurate, even if, when grossed up to a national level, they do not match those recorded as income by government providers.

## NHA Aggregate Data on Subsidies

A BIA requires National Health Account (NHA)—and potentially other—data on subsidies for each type of service for which utilization data are available. This NHA table typically has the title “Health Expenditures by Health Financing Agencies and Health Activities.” It shows the amount spent by government agencies (sometimes broken down by level of government and including any social health insurance agency) on inpatient care, outpatient care, and so forth.

## Notes

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1. See O'Donnell and others (2008) for a more comprehensive discussion.
2. For a descriptive analysis of inequalities in child survival, see, for example, Wagstaff (2000). For a decomposition of inequalities in child survival, see Hosseinpoor and others (2006).
3. See O'Donnell and others (2008, 182). If marginal effects are evaluated at values other than the sample mean, *different* results will emerge. The OLS decomposition, by contrast, is not vulnerable to this.
4. For a descriptive analysis of inequalities in malnutrition, see, for example, Wagstaff and Watanabe (2000). For a decomposition of inequalities in malnutrition, see Wagstaff, van Doorslaer, and Watanabe (2003).
5. See Wagstaff (2005, 2009); Erreygers (2009).
6. See, for example, d'Uva, O'Donnell, and van Doorslaer (2008).
7. See Das, Hammer, and Sánchez-Páramo (2010).

8. See O'Donnell and others (2008, 182).
9. See Das, Hammer, and Sánchez-Páramo (2010).
10. In principle, the standardization could be done without the nondemographic determinants, but it is not considered good practice because of the risk of omitted-variable bias.
11. In principle, the standardization could be done without the nondemographic determinants, but it is not considered good practice because of the risk of omitted-variable bias.

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## Example Data Set

The data sets used in all the tables and graphs in chapters 4–6 of the manual were produced using the 2006 Vietnam Household Living Standards Survey (VHLSS). Vietnam implemented two broad household surveys in 1993 and 1998 and, since 2002, has implemented surveys every second year, albeit with a slimmed-down health module compared to the 1993 and 1998 surveys. The attraction of the 2006 survey is that it included an extended health module.

Questions were asked on activities of daily living, self-assessed health, days lost due to illness, and other issues. The survey also asked about the use of different types of health provider (commune health centers, general hospitals, private facilities), with a distinction between outpatient and inpatient care. Information was also collected on the fees paid to public and private providers and on insurance coverage—Vietnam has a social health insurance scheme that covers formal sector workers out of contributions, civil servants and “people of merit” out of general revenues, and the poor (and other disadvantaged groups) also out of general revenues. Consumption in the survey is measured using an extensive set of modules capturing home production of food as well as market purchases of goods and services.

This chapter describes the variables used to generate the tables and graphs. ADePT produces basic descriptive statistics in an original data report, an example of which is presented in chapter 6.

## Household Identification

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ADePT asks first about the household identifier in the data set. In the VHLSS, several variables are needed to uniquely identify the households. These identify the province (*tin*), the district (*huyen*), the commune (*xa*), the village (*diaban*), and finally the family (*hoso*). Overall, the sample contains 39,071 individuals living in 9,189 households.

## Living Standards Indicators

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Living standards are measured by per capita household consumption (*pcexp*) measured in thousands of Vietnamese dong. This variable captures expenditures outside the household as well as home production of foodstuffs and the use value of consumer durables. The procedure follows previous multipurpose surveys in Vietnam.<sup>1</sup>

## Health Outcome Variables

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The VHLSS includes various measures of adult health status. We use nine variables of impairment in activities of daily living with respect to sight (*adleyesight*), hearing (*adlhearing*), memory (*adlmemory*), concentration (*adlconcent*), understanding (*adlunderstand*), walking in general (*adlwalk*), climbing stairs (*adlstairs*), walking 400 meters (*adl400m*), and climbing 10 steps (*adl10steps*). Other health status variables include whether the individual got sick or injured during the last four weeks (*illinj4wk*) and last 12 months (*illinj12m*), the number of days spent in bed due to health problems during the last 12 months (*beddays12m*), and the number of work or school days missed due to illness or injury during the last 12 months (*offwkdays12m*).

## Health Utilization Variables

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Health care utilization is measured by the number of outpatient visits over the previous 12 months to a general hospital (*opvis\_ghosp*), polyclinic (*opvis\_poly*), commune health center (*opvis\_chc*), village clinic (*opvis\_vill*), private facility (*opvis\_privfacil*), traditional healer (*opvis\_tradherb*), and other providers (*opvis\_othfacil*). There is also information on the

number of inpatient admissions over the same period to each of the aforementioned providers (*ipvis\_ghosp*, . . . , *ipvis\_othfacil*) and on the total fees paid by the individual for each of these health care utilization categories (*opexp\_ghosp*, . . . , *ipexp\_othfacil*).

## Variables for Basic Tabulations

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Other individual characteristics are also available, allowing us to analyze the health outcome and utilization variables conditional on them (in tables H2 and U2). These are individual age (*age*), a binary variable indicating gender (*male*), and a six-category education level (*educlev*).

## Weights and Survey Settings

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The survey design is quite complex, and a detailed description can be found in the basic information document, which is available on the World Bank's Living Standards Measurement Study website.<sup>2</sup> In order to get nationally representative statistics, we use the weight variable (*wt9*), which is provided along with the data collected.

## Determinants of Health

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The examples below use age and gender as the demographic variables and per capita household consumption as the control variable.

## Determinants of Utilization

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The indicators of need include age and gender as well as the health indicators mentioned above. In the decompositions seeking to explain inequality, two non-need variables are included. The first is health insurance. This is measured through three binary variables indicating whether the individual is covered by health insurance for the poor (*hi\_poor*), mandatory health insurance (*hi\_comp*), or voluntary health insurance (*hi\_vol*). The second non-need variable used in the decomposition analysis is government per

capita health expenditure. This is measured at the provincial level (*ghe\_cap*) and has been merged into the data set from provincial government expenditure files.

### **Utilization Variables for Benefit Incidence Analysis**

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For the benefit incidence analysis (BIA), the following utilization variables are used: outpatient visits to a commune health center (CHC), polyclinic, and general hospital and inpatient admissions to a general hospital.

### **Fees Paid to Public Providers**

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For each outpatient visit and inpatient admission, the VHLSS records the out-of-pocket payments associated with the visit. The recorded data—unlike the official data on fees kept by the ministry—include informal payments and transport costs: respondents in the VHLSS are asked to include “payments for medical service and treatment,” but also “other related costs (for example, bonus for doctors, transport).” Unfortunately, there is no way to exclude transport costs from the household data.

### **NHA Aggregate Data on Subsidies**

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Government spending (that is, subsidies) on public facilities is in millions of dong and relates to 2005, the closest year to 2006 for which detailed National Health Account (NHA) data are available. The data are taken from NHA table 2.<sup>3</sup> The government spending figures reflect spending by the health ministry and the central government, by health departments at the provincial and district levels, as well as by the social health insurance agency, Vietnam Social Security. The table does not break government spending down exactly by type of provider. The assumption is that spending on “traditional medicine” is all at the hospital level. Government spending on inpatient care is taken from the figures labeled “inpatient treatment” and “outpatient treatment” under the “traditional medicine” heading—that is, items HD 1.1.1 and HD 1.1.2, respectively. Spending at the CHC and polyclinic level is taken from the heading “primary health care and school

health care” under “health prevention and public health”—that is, item HD 1.2.4. This is the only item in the NHA where spending at the commune level is recorded, but it is possible that some of the polyclinic spending is recorded at a higher level. It is assumed that 75 percent of the “primary health care and school health care” spending was incurred in health facilities and the rest was incurred in schools.

## Notes

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1. At the time of writing, the basic information document for the 2006 survey was not available. However, the survey is similar to the 2002 and 2004 VHLSS, for which a (combined) basic information document is available at <http://www.worldbank.org/lsms>.
2. <http://www.worldbank.org/lsms>.
3. Vietnam Ministry of Health (2008, 135). See [http://www.wpro.who.int/NR/rdonlyres/69A8189E-92ED-4883-ABEC-B90CBE894522/0/National\\_Health\\_Account.pdf](http://www.wpro.who.int/NR/rdonlyres/69A8189E-92ED-4883-ABEC-B90CBE894522/0/National_Health_Account.pdf).

## Reference

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Vietnam Ministry of Health. 2008. *National Health Account: Implementation in Viet Nam; Period from 2000–2006*. Hanoi: Statistical Publishing House.



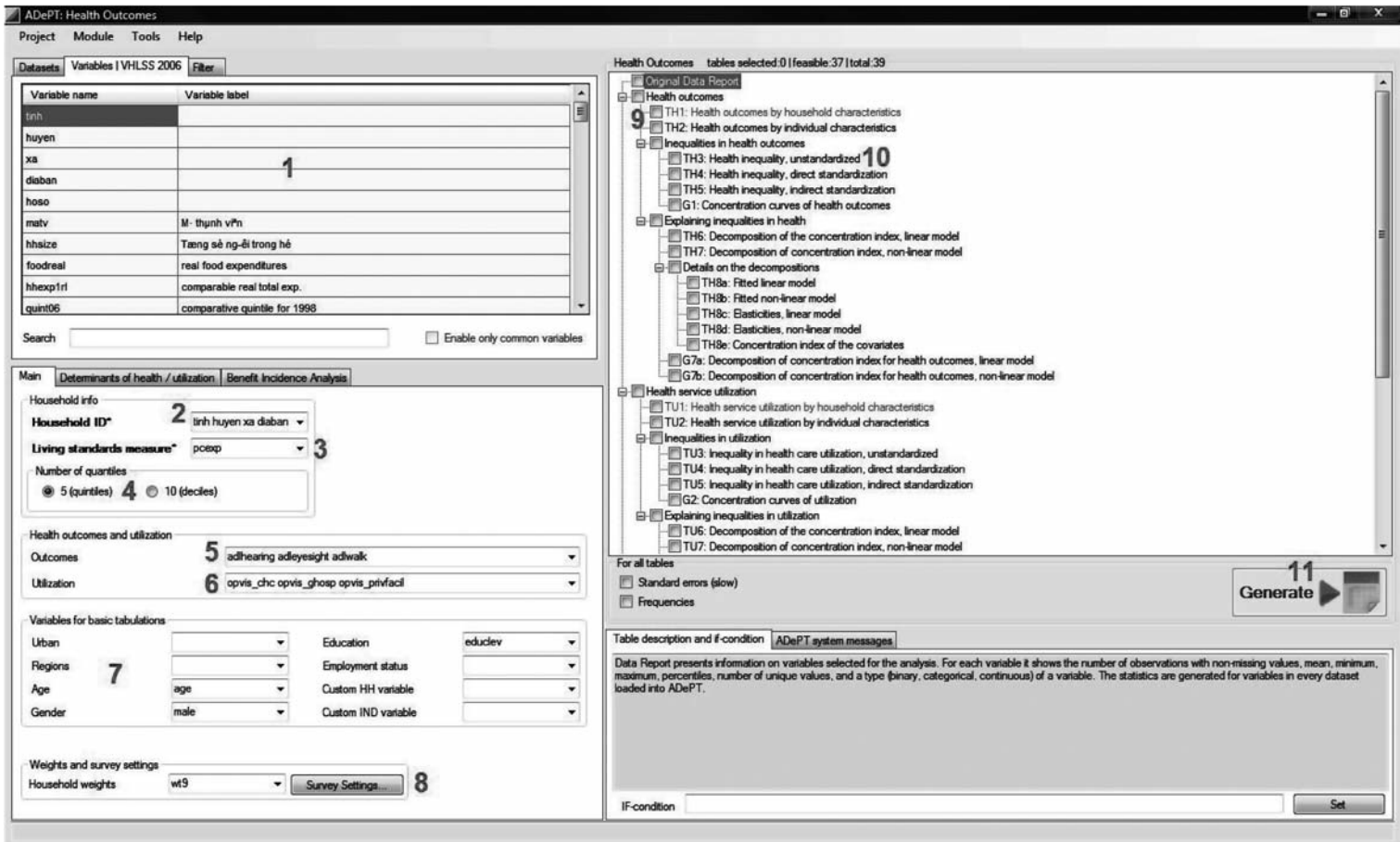
# How to Generate the Tables and Graphs

This chapter explains how to set up ADePT Health Outcomes so as to generate tables and graphs. The assumption is that the data set has been prepared *before* it is loaded into ADePT. The explanation proceeds with a screen shot of ADePT, with numbers on the screenshot corresponding to the steps outlined.

# Main Tab

All users will need to enter information on the “main” tab as follows.

Screenshot 5.1: Main Tab





1. Start up ADePT, select the Health Outcomes module, add a data set (click on the “add” button), and then label it (type a name in the box).  
*Hint 1: If you have used ADePT before, your previous session will be reloaded. You have three options in this case: (1) Continue with the same data set, in which case just keep going. (2) Do the same type of analysis you were doing before but for a different data set with variables labeled the same. In this case, simply “remove” the data set, “add” your new data set, and continue. All the boxes in which you previously entered information will still include the information. If, while running, ADePT finds that your new data set does not include some of the variables, it will mark them in red in the user interface. (3) Start with a new analysis and a new data set. In this case, simply choose Project -> Reset or hit ctrl-R. Hint 2: You can load several data sets into ADePT at once. The variables you want to analyze will need to exist and be similarly named in both data sets. To facilitate this, check the “enable only common variables” box; this will cause ADePT to show only the variables that appear in all the data sets you have loaded.*
2. Click on the “variables” tab at the top left corner of the ADePT screen and then the “main” tab in the bottom left corner of the ADePT screen. Next provide the household identifier variable (or *variables*—AdePT can accommodate multiple variables in the household identification, ID, box). ADePT checks the uniqueness of identification and issues a warning message when required. You can input your household ID variables in the household ID box (*and other variables in other boxes*) either by dragging the variable from the list of variables at the top left of the screen or by selecting the variable(s) from the drop-down menu. *Hint: You can simplify the dragging approach by typing part of the name of the variable(s) in the “search” box; ADePT will then show only those variables whose name includes the text you typed in the search box.*
3. Enter the name of the living standards indicator. This is typically a measure of per capita or “equivalent” household income or consumption. *Hint: You need to have expressed the household living standards indicator on a per capita or equivalent basis before loading the data into ADePT.*
4. Indicate whether the tables should present quintiles or deciles.
5. Enter the name of the *health outcome* variables to be analyzed. These could be binary (for example, having a particular health condition or not), categorical (for example, self-assessed health), cardinal (for example, number of work days missed due to sickness), or continuous but not cardinal (for example, anthropometric z scores).
6. Enter the names of the *health care utilization* variables to be analyzed. These are typically a binary variable (for example, whether a consultation occurred during a specified period) or a count variable (for example, the number of consultations).
7. Optionally, enter categorical or discrete individual- or household-level variables by which you would like outcomes or utilization to be tabulated. ADePT invites users to enter variables capturing whether the household lives in an urban setting, the region it lives in, and the individual’s age, his or her gender, level of education, and employment status.
8. Provide household weights. If necessary, also set the appropriate survey settings by clicking on “survey settings.”
9. If you want tabulations by the variables entered in step 7, check the boxes TH1 and TH2, TU1 and TU2, or both.
10. If you want unstandardized inequalities in health outcomes or utilization, check the boxes against TH3 (and perhaps G1) or against TU3 (and perhaps G2). These provide standardized distributions of health outcomes and utilization, respectively.
11. If you want *only* these tables and graphs, hit the “generate” button to start the computation and generate the selected outputs. Otherwise continue to the “determinants of health” tab to enter information enabling inequalities to be explained or the “benefit incidence analysis (BIA)” tab to enter the information necessary for a BIA.

## Determinants of Health or Utilization

ADePT users wanting to explain inequalities in health or utilization should enter information on the “main” tab as outlined above before entering the necessary information on the “determinants of health or utilization” tabs. Users wanting to undertake only a BIA should proceed directly to the “benefit incidence analysis” tab after the “main” tab.

**Screenshot 5.2: Inequalities in Health or Utilization Tab**

**ADePT: Health Outcomes**

Project Module Tools Help

Datasets Variables | VHLSS 2006 Filter

Variable name	Variable label
linh	
huyen	
xa	
diaban	
hoso	
matv	M- thưng vPh
hhsaize	Tæng sè ng-đi trong hê
foodreal	real food expenditures
hhexp1r1	comparable real total exp.
quint06	comparative quintile for 1998

Search:  ☐ Enable only common variables

Main Determinants of health / utilization Benefit Incidence Analysis

**Determinants of health**

☒ Standardizing (demographic) variables 1

male age

☒ Control variables 2

pexp

**Determinants of utilization**

☒ Standardizing (fixed) variables 3

adeyesight adhearing admemory adconcent adunderstand adwalk adstairs ad400m ad10steps male age

☒ Control variables 4

pexp ghe\_cap hi\_poor hi\_comp hi\_vol

**Health Outcomes** tables selected 0 / feasible 37 / total 39

- Original Data Report
- Health outcomes
  - TH1: Health outcomes by household characteristics
  - TH2: Health outcomes by individual characteristics
- Inequalities in health outcomes
  - TH3: Health inequality, unstandardized
  - TH4: Health inequality, direct standardization
  - TH5: Health inequality, indirect standardization
  - G1: Concentration curves of health outcomes
- Explaining inequalities in health
  - TH6: Decomposition of the concentration index, linear model
  - TH7: Decomposition of concentration index, non-linear model
  - Details on the decompositions
    - TH8a: Fitted linear model
    - TH8b: Fitted non-linear model
    - TH8c: Elasticities, linear model
    - TH8d: Elasticities, non-linear model
    - TH8e: Concentration index of the covariates
  - G7a: Decomposition of concentration index for health outcomes, linear model
  - G7b: Decomposition of concentration index for health outcomes, non-linear model
- Health service utilization
  - TU1: Health service utilization by household characteristics
  - TU2: Health service utilization by individual characteristics
- Inequalities in utilization
  - TU3: Inequality in health care utilization, unstandardized
  - TU4: Inequality in health care utilization, direct standardization
  - TU5: Inequality in health care utilization, indirect standardization
  - G2: Concentration curves of utilization
- Explaining inequalities in utilization
  - TU6: Decomposition of the concentration index, linear model
  - TU7: Decomposition of concentration index, non-linear model

For all tables

☐ Standard errors (slow) 6

☐ Frequencies 7

10 **Generate**

Table description and if-condition ADePT system messages

Data Report presents information on variables selected for the analysis. For each variable it shows the number of observations with non-missing values, mean, minimum, maximum, percentiles, number of unique values, and a type (binary, categorical, continuous) of a variable. The statistics are generated for variables in every dataset loaded into ADePT.

IF-condition 8  **Set**

1. Optionally, check the box to indicate that standardizing variables for health outcomes are to be entered and enter the variable names. These might be demographic variables (such as age and gender) for which income-related health inequality is *not* deemed inequitable. *Hint: Which variables to include here is a matter of debate; there is no right or wrong answer!*
2. Optionally, check the box to indicate that control variables for health outcomes are to be entered and enter the variable names. These are factors (such as income and health insurance) for which income-related health inequality is deemed unjustified. Note that these variables need to be specified appropriately. For instance, a categorical variable such as education should be included as a set of indicator (or dummy) variables, one per education level, with the exception of a reference category. *Hint: A quick way to do this is to put an "i." in front of the categorical variable. For example, if educn is a categorical education variable, you can force ADePT to treat it as a series of summary variables corresponding to the categories by inserting i.educn in the control variable box.*
3. Optionally, check the box to indicate that standardizing variables for utilization are to be entered and enter the variable names. These are typically health care need variables (such as demographic and health status variables) for which income-related inequality in health care utilization is *not* deemed inequitable. *Hint: The health status "need" variables might well be the same variables as the ones specified in step 9, if any, but the user needs to decide this and copy and paste the information if this is what is desired.*
4. Optionally, check the box to indicate that control variables for utilization are to be entered and enter the variable names. These are factors (such as income and health insurance) for which income-related inequality in health care utilization *is* deemed unjustified.
5. Select which tables are to be generated. Tables H4 and H5 provide the direct and indirect standardization results for health outcomes. Tables H6 and H7 provide decompositions of inequalities in health outcomes. Table H8 provides details of these decompositions. Tables U4 and U5 provide the direct and indirect standardization results for health utilization. Tables U6 and U7 provide decompositions of inequalities in utilization. Table U8 provides details of the decompositions.
6. Specify whether the standard error of each indicator is to be produced. This is required for inference but slows down computation.
7. Check the "frequencies" box if you want an additional page in the spreadsheet showing the frequencies (that is, number of cases) used to compute each statistic requested.
8. To produce a table or figure for a *subset of cases*, highlight the relevant table or graph and enter the relevant "if condition" in the "if condition" box. *Hint: Each table or graph can have a different "if condition" assigned to it.*
9. If you want *all* the analysis to be done for just a subset of cases, click on the "filter" tab, check the "keep observations if" box, and enter the desired condition.
10. Hit the "generate" button to start the computation and generate the selected outputs.

## Benefit Incidence Analysis

ADePT users wanting to undertake a benefit incidence analysis should enter information on the “main” tab as outlined above before proceeding to the “benefit incidence analysis” tab.

**Screenshot 5.3: Benefit Incidence Analysis Tab**

**ADePT: Health Outcomes**

Project Module Tools Help

Datasets Variables | VHLSS 2006 Filter **11**

Variable name	Variable label
inh	
huyen	
xa	
diaban	
hoso	
matv	M- thynh vfn
hhsz	Tæng sè ng-êi trong hê
foodreal	real food expenditures
hhexp1rl	comparable real total exp.
quint06	comparative quintile for 1998

Search  ☐ Enable only common variables

Main Determinants of health / utilization **Benefit Incidence Analysis**

☐ Dataset only has total out-of-pocket **1**

Utilization quantity\* **2**

Fee (OOP)\* **3**

Aggregate subsidy\* **4**

Utilization quantity	Fee (OOP)	Aggregate subsidy
opvis_chc	opexp_chc	162481000
opvis_poly	opexp_poly	21898000
opvis_ghosp	opexp_ghosp	3971381000
ipadm_ghosp	ipexp_ghosp	3276459000

**6**

Add **5** Remove

Health Outcomes tables selected:0 / feasible:37 / total:39

- TH8e: Concentration index of the covariates
- G7a: Decomposition of concentration index for health outcomes, linear model
- G7b: Decomposition of concentration index for health outcomes, non-linear model
- Health service utilization
  - TU1: Health service utilization by household characteristics
  - TU2: Health service utilization by individual characteristics
  - Inequalities in utilization
    - TU3: Inequality in health care utilization, unstandardized
    - TU4: Inequality in health care utilization, direct standardization
    - TU5: Inequality in health care utilization, indirect standardization
    - G2: Concentration curves of utilization
  - Explaining inequalities in utilization
    - TU6: Decomposition of the concentration index, linear model
    - TU7: Decomposition of concentration index, non-linear model
  - Details on the decompositions
    - TU8a: Fitted linear model
    - TU8b: Fitted non-linear model
    - TU8c: Elasticities, linear model
    - TU8d: Elasticities, non-linear model
    - TU8e: Concentration index of the covariates
  - G8a: Decomposition of concentration index for utilization values, linear model
  - G8b: Decomposition of concentration index for utilization values, non-linear model
- Benefit Incidence Analysis **7**
  - TS1: Utilization of public facilities
  - TS2: Payments to public providers
  - TS3: Health care subsidies, constant unit cost assumption
  - TS5: Health care subsidies, constant unit subsidy assumption
  - TS4: Health care subsidies, proportional cost assumption
  - G3: Concentration curves of subsidies, constant unit cost assumption
  - G5: Concentration curves of subsidies, constant unit subsidy assumption
  - G4: Concentration curves of subsidies, proportional cost assumption

For all tables

☐ Standard errors (slow) **8**

☐ Frequencies **9**

**12** Generate

Table description and if-condition ADePT system messages

Data Report presents information on variables selected for the analysis. For each variable it shows the number of observations with non-missing values, mean, minimum, maximum, percentiles, number of unique values, and a type (binary, categorical, continuous) of a variable. The statistics are generated for variables in every dataset loaded into ADePT.

IF-condition **10** Set

1. Fill out this field when disaggregated information on out-of-pocket expenditure is not available. When this is filled out, the individual fee per health care category no longer has to be entered (that is, step 3 becomes unnecessary).
2. One health care category at a time, follow steps 2 to 5. Start by specifying the variable containing the number of health care units used by each individual (for example, number of outpatient visits in a general hospital). *Hint: If you are going to do a BIA with the utilization variables, make sure that these are scaled to refer to the same period.*
3. Enter the variable measuring the individual fee paid for the corresponding unit of utilization.
4. Type in the total public subsidy allocated for the category of utilization in question. This is an aggregate value found in National Health Account macro data.
5. Click on the “add” button.
6. Information from steps 2–4 should appear on the list. It is possible to remove any element of the list and repeat steps 2–5 to enter information related to additional health care categories.
7. Select which tables and graphs are to be generated. Relevant ones for BIA are tables S1–S5 and graphs G3–G5. Some of the tables might not be available depending on the information provided to ADePT.
8. Specify whether the standard error of each indicator is to be produced. This is required for inference, but slows down computation.
9. Check the “frequencies” box if you want an additional page in the spreadsheet showing the frequencies (that is, number of cases) used to compute each statistic requested.
10. To produce a table or figure for a *subset of cases*, highlight the relevant table or graph and enter the relevant “if condition” in the “if condition” box. *Hint: Each table or graph can have a different “if condition” assigned to it.*
11. If you want *all* the analysis to be done for just a subset of cases, instead click on the “filter” tab, check the “keep observations if” box, and enter the desired condition.
12. Hit the “generate” button to start the computation and generate the selected outputs.



# Interpreting the Tables and Graphs

As detailed in chapter 4, all of the tables and graphs in this chapter were produced using data from the 2006 Vietnam Household Living Standards Survey.

## Original Data Report

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### Concepts

The original data report gives basic statistics on the variables provided by users and shows in parentheses the field in which each variable was entered. This report is important as it makes it possible to detect many of the bold errors that may occur when preparing the data. For each variable, the first column shows the number of observations with a valid value (that is, a value that is not represented by a missing value in Stata). The next three columns present the mean, minimum, and maximum values of each variable. Column “p1” gives the first percentile—in other words, the value that is greater than 1 percent of the values taken by the variable (and thus smaller than 99 percent of its values). Column “p50” represents the median, and “p99” represents the 99th percentile. The last column indicates the number of different values taken by each variable.

## Original Data Report

	<i>N</i>	<i>mean</i>	<i>min</i>	<i>max</i>	<i>p1</i>	<i>p50</i>	<i>p99</i>	<i>N_unique</i>
<b>VHLSS 2006</b>								
tinh (Household ID)	39,071	460	101	823	101	411	823	64
huyen (Household ID)	39,071	10.7	1.0	53.0	1.0	9.0	43.0	35.0
xa (Household ID)	39,071	18.2	1.0	95.0	1.0	15.0	63.0	57
diaban (Household ID)	39,071	10.1	1.0	105.0	1.0	8.0	42.0	59.0
hoso (Household ID)	39,071	14.6	13.0	25.0	13.0	14.0	20.0	10
pcexp (Welfare aggregate)	39,071	5,481	554	153,995	1,076	4,369	21,180	9,185
wt9 (Household weights)	39,071	2,111	467	4,637	576	2,006	4,353	2,079
adlhearing (Outcome 1)	36,701	0.0	0.0	1.0	0.0	0.0	1.0	2.0
adleyesight (Outcome 2)	36,701	0.1	0.0	1.0	0.0	0.0	1.0	2.0
adlwalk (Outcome 3)	36,701	0.1	0.0	1.0	0.0	0.0	1.0	2.0
opvis_chc (Custom category 1)	39,071	0.3	0.0	80.0	0.0	0.0	6.0	30
opvis_ghosp (Custom category 2)	39,071	0.4	0.0	52.0	0.0	0.0	6.0	32.0
opvis_privfacil (Custom category 3)	39,071	0.4	0.0	80.0	0.0	0.0	8.0	34
opvis_chc (Custom category 1)	39,071	0.3	0.0	80.0	0.0	0.0	6.0	30.0
opexp_chc (Custom category 1)	39,071	7.0	0.0	3,600	0.0	0.0	150.0	182
opvis_poly (Custom category 2)	39,071	0.0	0.0	40.0	0.0	0.0	1.0	19.0
opexp_poly (Custom category 2)	39,071	2.5	0.0	22,000	0.0	0.0	10.0	83
opvis_ghosp (Custom category 3)	39,071	0.4	0.0	52.0	0.0	0.0	6.0	32.0
opexp_ghosp (Custom category 3)	39,071	64.0	0.0	105,600	0.0	0.0	1,400	425
ipadm_ghosp (Custom category 4)	39,071	0.1	0.0	13.0	0.0	0.0	2.0	12.0
ipexp_ghosp (Custom category 4)	39,071	103.7	0.0	60,000	0.0	0.0	2,500	342
age (Age)	39,071	31.0	0.0	108.0	0.0	27.0	82.0	104.0
male (Gender)	39,071	1.5	1.0	2.0	1.0	2.0	2.0	2.0
educlev (Education)	39,071	1.4	0.0	5.0	0.0	1.0	5.0	6.0
generated (Household size)	39,071	4.9	1.0	17.0	2.0	5.0	10.0	16

Source: Authors.

## Interpreting the Results

Provided that they have been adequately prepared, the identification (ID) variables generally give the number of observations in the sample analyzed, which amounts to 39,071 in our example table. For instance, per capita expenditure (*pcexp*) also has 39,071 observations and thus does not contain any missing values. Mean per capita expenditure amounts to D5.5 million (*pcexp* is measured in thousands of Vietnamese dong) and ranges from D554,000 to D154 million. The median (D4.4 million) is smaller than the mean, which indicates the expected right-skewed distribution of living standards variables. The last column of the table usually makes it possible to identify categorical data. For instance, our three outcome variables, *adlhearing*, *adleyesight*, and *adlwalk*, appear to be binary, as they are shown to take only two different values.



## Basic Tabulations

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### Concepts

Compared with ADePT's original data report, which provides basic summary statistics on all variables specified, tables H1, H2, U1, and U2 provide more in-depth descriptive analysis of the health variables. Tables H1 and H2 relate to health outcomes, while tables U1 and U2 display health utilization variables. All these tables show the mean of the health variables according to household (H1 and U1) and individual (H2 and U2) characteristics. ADePT also computes standard errors, which are presented in parentheses below the corresponding means. Under the assumption of normal distribution, subtracting twice the standard error from the mean, and then adding twice the standard error to the mean, yields the 95 percent confidence interval. This interval, which is reported in many standard Stata outputs, has a 95 percent chance of containing the true (and unknown) value of interest.

### Interpreting the Results

All tables are read in the same way. We show here only one example, table H2, which presents the relation between health outcomes and individual characteristics. The health outcomes analyzed are binary variables indicating whether the individual suffers from impairment in activities of daily living with respect to hearing, seeing, and walking. Individual characteristics are a binary indicating gender, age divided into 13 classes, and education level ranging from 0 (lowest) to 5 (highest).

In general, women have more health problems than do men. For instance, the prevalence of walking impairment amounts to 4.7 percent for men and 7.3 percent for women. Given the very small standard errors, such a differential is statistically significant. Table H2 also shows the expected increase in health problems with age. Age is a continuous variable that ADePT expresses as age categories in this description, but we treat age as continuous in the following analyses. Finally, the relationship between health and education is less clear-cut. However, the least educated individuals, in general, have the highest prevalence of health impairment. Health impairment does not continuously decrease with education, though. For instance, the two highest education levels show a fairly high prevalence of impaired sight.

**Table H2: Health Outcomes by Individual Characteristics**

	<i>adlhearing</i>	<i>adleyesight</i>	<i>adlwalk</i>
<b>Gender</b>			
Male	0.031 (0.0014)	0.102 (0.0024)	0.047 (0.0017)
Female	0.035 (0.0014)	0.125 (0.0026)	0.073 (0.0021)
<b>Age</b>			
0–5	0.000 (0.0000)	0.002 (0.0017)	0.029 (0.0073)
6–14	0.005 (0.0009)	0.017 (0.0017)	0.005 (0.0008)
15–19	0.006 (0.0011)	0.024 (0.0024)	0.008 (0.0013)
20–24	0.007 (0.0015)	0.022 (0.0028)	0.009 (0.0016)
25–29	0.007 (0.0019)	0.017 (0.0032)	0.011 (0.0022)
30–34	0.005 (0.0014)	0.016 (0.0028)	0.010 (0.0021)
35–39	0.009 (0.0018)	0.020 (0.0029)	0.018 (0.0026)
40–44	0.010 (0.0019)	0.072 (0.0051)	0.029 (0.0032)
45–49	0.016 (0.0024)	0.159 (0.0074)	0.047 (0.0044)
50–54	0.034 (0.0044)	0.235 (0.0097)	0.068 (0.0060)
55–59	0.058 (0.0062)	0.318 (0.0129)	0.130 (0.0094)
60–64	0.092 (0.0097)	0.409 (0.0166)	0.199 (0.0139)
65+	0.249 (0.0085)	0.559 (0.0097)	0.414 (0.0097)
<b>Education level</b>			
0	0.072 (0.0027)	0.180 (0.0040)	0.122 (0.0034)
1	0.022 (0.0015)	0.085 (0.0030)	0.041 (0.0021)
2	0.016 (0.0014)	0.075 (0.0031)	0.033 (0.0021)
3	0.008 (0.0017)	0.068 (0.0047)	0.024 (0.0030)
4	0.024 (0.0032)	0.136 (0.0070)	0.050 (0.0046)
5	0.014 (0.0035)	0.146 (0.0108)	0.035 (0.0055)
<b>Total</b>	0.033 (0.0010)	0.114 (0.0018)	0.060 (0.0013)

Source: Authors.

## Inequalities in Health Outcomes

### Concepts

Tables H3–H5 show the distribution and concentration of health according to income or any other measure of socioeconomic status. Table H3 presents the unstandardized distribution of health, whereas the other two present standardized distributions using the direct and indirect methods. The idea of standardization is to eliminate the inequality arising from variables that are beyond the control of policy makers, notably demographic factors such as age and gender. Since standardization can be achieved in a more transparent way by means of the decomposition of the concentration index (see technical note 7 in chapter 7), we do not present tables H4 and H5 here. However, ADePT makes it possible to generate these tables; for more information, see O'Donnell and others (2008, ch. 5).

The first part of the tables gives the average health status per quintile along with standard errors, which are presented in parentheses below each

**Table H3: Health Inequality, Unstandardized**

	<i>adlhearing</i>	<i>adleyesight</i>	<i>adlwalk</i>
<b>Quintiles of pcexp</b>			
Lowest quintile	0.0346 (0.0022)	0.0820 (0.0033)	0.0589 (0.0029)
2	0.0380 (0.0023)	0.1043 (0.0037)	0.0613 (0.0029)
3	0.0352 (0.0023)	0.1111 (0.0038)	0.0578 (0.0029)
4	0.0285 (0.0021)	0.1219 (0.0041)	0.0604 (0.0030)
Highest quintile	0.0283 (0.0022)	0.1469 (0.0047)	0.0633 (0.0033)
Total	0.0329 (0.0010)	0.1136 (0.0018)	0.0603 (0.0013)
Standard concentration index	−0.0583 (0.0175)	0.1096 (0.0090)	0.0147 (0.0132)
Conc. index with inequality-aversion parameter = 3	−0.0784 (0.0268)	0.1604 (0.0130)	0.0157 (0.0198)
Conc. index with inequality-aversion parameter = 4	−0.0834 (0.0340)	0.1934 (0.0159)	0.0165 (0.0246)
Standard achievement index	0.0348 (0.0084)	0.1012 (0.0075)	0.0594 (0.0098)
Achievement index with inequality-aversion parameter = 3	0.0354 (0.0096)	0.0954 (0.0076)	0.0594 (0.0100)
Achievement index with inequality-aversion parameter = 4	0.0356 (0.0108)	0.0916 (0.0081)	0.0593 (0.0100)

Source: Authors.

average. The concentration index is then displayed for three different values of the inequality-aversion parameter. The concentration index is a measure of how health status is related to income. A positive value indicates that the health variable is more concentrated among richer individuals. In the case of a variable for ill health, such as impairment in activities of daily living, a positive value of the concentration index means that the rich are in worse health than the poor. A negative value indicates the opposite, whereas a concentration index not very different from 0 reflects no relationship between income and health status.

The standard concentration index implicitly gives the poorest individual a weight close to 2, and the weight decreases linearly to reach a value close to 0 for the richest individual. A more general measure of concentration, the extended concentration index, makes it possible to change this weighting by setting the value of an inequality-aversion parameter. When the inequality-aversion parameter equals 2, the extended concentration index equals the concentration index. When the parameter is increased (here to 3 and 4), more weight is given to the poorest individual, and this weight decreases faster than linearly to reach 0 for the richest individual (see technical note 4 in chapter 7 for more details).

The last three lines of the tables display the achievement index (presented in technical note 5 in chapter 7), which is a measure of average health taking health inequality into account: the greater the health inequality, the smaller is the achievement index. It can be shown that the achievement index equals average health multiplied by the factor 1 minus the extended concentration index. It is thus also sensitive to the degree of aversion to inequality, and the corresponding parameter appears in parentheses.

### Interpreting the Results

Our example table H3 shows the income-related inequality in three health status variables. These are binary variables indicating whether the individual suffers from impairment in activities of daily living with respect to hearing, seeing, and walking. On average, 3.46 percent of the first quintile experience hearing problems. This amounts to 8.20 and 5.89 percent for seeing and walking, respectively. Starting with the second quintile, the prevalence of hearing impairment decreases with income, but seeing impairment increases with income, and walking impairment seems largely independent of income.

The table also shows the average prevalence in the whole population, which amounts to 3.29, 11.36, and 6.03 percent for limitations in hearing, seeing, and walking, respectively. The concentration index for hearing is moderately negative ( $-0.0583$ ), which reflects the decrease in health conditions with income. In contrast, the concentration index for seeing impairment is clearly positive ( $0.1096$ ) as a result of the increase in prevalence with income. Finally, the concentration index for walking ( $0.0147$ ) is close to 0, which indicates near independence between this health condition and income.

When aversion to inequality is increased, the weight of the first quintiles is increased relative to the richest quintiles. Since the first quintiles have a higher prevalence of hearing impairment, the corresponding extended concentration index gets farther into the negatives. The opposite is true for seeing impairment, and the extended concentration index for walking impairment is barely affected by change in inequality aversion.

Finally, the achievement index amounts to 0.0348, 0.1012, and 0.0594 for hearing, seeing, and walking impairment, respectively, when applying the standard concentration index weighting. These have to be compared with the nonweighted averages for the whole population. For instance, since the concentration index is positive in the case of seeing impairment, the relatively higher prevalence of the richest is underweighted, and, as a result, the achievement index ( $0.1012$ ) indicates better health compared with average health ( $0.1136$ ).

When aversion to inequality is increased (that is, the last two lines of the table), the greater weight assigned to the first quintiles makes average health deteriorate slightly in the case of hearing (that is, higher average prevalence of hearing impairment). In contrast, as richer individuals suffer more from seeing impairment, higher aversion to inequality makes the achievement index improve for this condition (that is, lower average prevalence of seeing impairment).

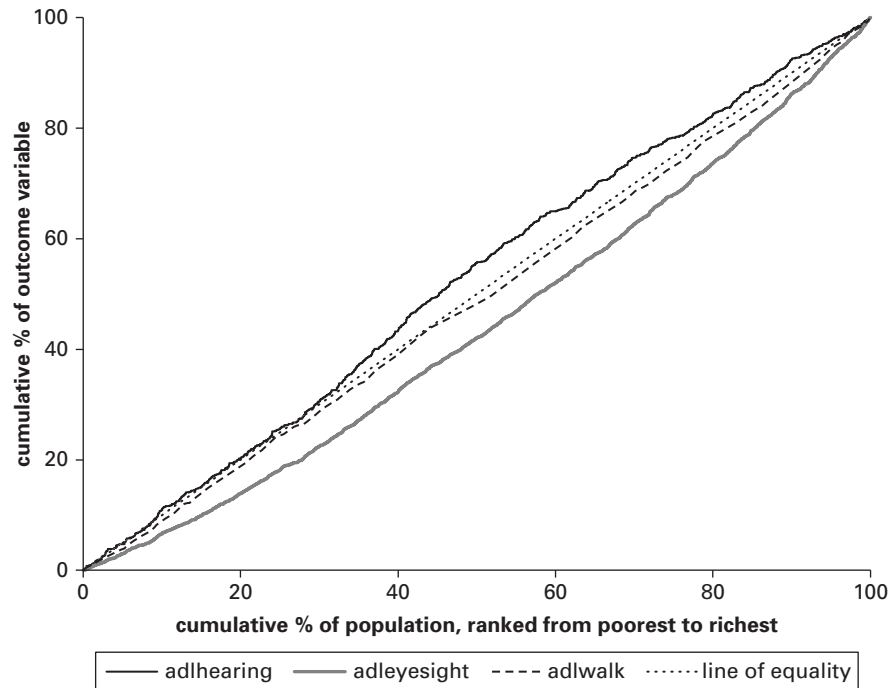
## Concentration of Health Utilization

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### Concepts

Graphs G1 and G2 present the concentration curve for each health outcome and for utilization of each health service analyzed, respectively. The curves represent the cumulative share of either health outcomes or utilization

**Graph G1: Concentration Curves of Health Outcomes**



Source: Authors.

according to the cumulative share of population, ranked by increasing consumption. For instance, the poorest 30 percent might suffer from 50 percent of total health conditions. These curves show how health outcomes or utilization vary according to consumption: the farther a curve is above the 45° line, the more the corresponding health variable is concentrated among the poorest households. When the concentration curve lies under the 45° line, the corresponding health variable is more concentrated among the richest households. Twice the area between the concentration curve and the 45° line equals the concentration index, the values of which are presented in table H3 for health outcomes and table U3 for utilization.

### Interpreting the Results

Our example graph G1 shows the income-related inequality in three health status variables. These are binary variables indicating whether the individual

suffers from impairment in activities of daily living with respect to hearing, seeing, and walking. The concentration curve for hearing impairment lies above the 45° line, which confirms that this health condition is more prevalent among the poor. By contrast, the concentration curve for seeing impairment lies below the 45° line, which means that this health condition is more concentrated among the rich. The concentration curve for walking limitations is very close to the 45° line, which indicates very little association between this health condition and income.

## Explaining Inequalities in Health

### Concepts

Tables H6 and H7 show two alternatives for the decomposition of the health concentration index by health determinant. In these tables, it is possible to distinguish inequality (the extent to which health is linked to income) from inequity (the part of inequality deemed unjustified) by separating the factors into two different groups. On the one hand, the standardizing variables are the variables whose correlation with health is deemed justifiable. Demographic factors such as age and gender are common examples of such variables. On the other hand, control variables are the factors whose correlation with health is deemed unfair. These variables “control” health standardization in the sense that they prevent standardizing variables from picking up the effect of variables with which they are correlated. Moreover,

**Table H6: Decomposition of the Concentration Index for Health Outcomes, Linear Model**

	<i>adlhearing</i>	<i>adleyesight</i>	<i>adlwalk</i>
<b>Standardizing (demographic) variables</b>			
male	0.0002	−0.0002	−0.0009
age	0.1036	0.0802	0.0971
Subtotal	0.1038	0.0801	0.0962
<b>Control variables</b>			
pcexp	−0.1015	0.0256	−0.0405
Subtotal	−0.1015	0.0256	−0.0405
Residual	−0.0606	0.0040	−0.0411
Inequality (total)	−0.0583	0.1096	0.0147
Inequity / Unjustified inequality	−0.1621	0.0295	−0.0816

Source: Authors.

in addition to standardization, the decomposition also makes it possible to quantify the contribution of both standardizing and control variables to overall health inequality.

Tables H6 and H7 also show total income-related inequality caused by standardizing variables (the first subtotal) and by control variables (the second subtotal). When the part of income-related inequality that is not explained by the chosen determinants (that is, the residual) is added to these two subtotals, the overall inequality is obtained—line “inequality (total)” in the table. Finally, when we subtract the justifiable inequality (that is, the first subtotal) from the overall inequality, we obtain the unjustified inequality—in other words, the inequity in income-related inequality.

For the decomposition the health variable needs to be regressed on standardizing and control variables. When the health variable is continuous, a linear model is often acceptable and it is possible to estimate the parameters by ordinary least squares (OLS). The result of this estimation is presented in table H8a, and the corresponding decomposition of the concentration index is presented in table H6. However, most health variables are better estimated by a nonlinear model, as health is often measured as a binary variable (for example, having a particular health condition or not), as an ordinal variable (for example, self-assessed health), or as counts (for example, number of days spent in bed due to illness). ADePT is usually able to determine the best nonlinear model to be estimated, and the result of this estimation is displayed in table H8b. The decomposition of

**Table H8a: Fitted Linear Model**

	<i>adlhearing</i>		<i>adleyesight</i>		<i>adlwalk</i>	
	<i>coef</i>	<i>se</i>	<i>coef</i>	<i>se</i>	<i>coef</i>	<i>se</i>
<b>Standardizing (demographic) variables</b>						
male	−0.0023	0.0019	0.0056*	0.0032	0.0151***	0.0024
age	0.0028***	0.0001	0.0074***	0.0001	0.0048***	0.0001
<b>Control variables</b>						
pcexp	−1.59E-06***	2.05E-07	1.38E-06***	4.48E-07	−1.16E-06***	3.13E-07
Intercept	−0.0468***	0.0036	−0.1506***	0.0058	−0.1149***	0.0048
Number of observations	36,701		36,701		36,701	
Adjusted R <sup>2</sup>	0.09		0.21		0.16	

Source: Authors.

Note: \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.



the concentration index corresponding to this nonlinear model is then presented in table H7.

Each contribution in the decomposition is the product of the sensitivity of health with respect to the corresponding determinant and the degree of income-related inequality in that determinant. Sensitivity is measured by the elasticity of health according to the determinants. These elasticities are computed with the estimated model and are presented in table H8c for the linear model and in table H8d for the nonlinear model. Finally, income-related inequality is measured with the concentration index of the determinants. These concentration indexes are displayed in table H8e. Since they do not rely on the estimated model, they are common to the decompositions in tables H6 and H7.

Using a nonlinear model is not an ideal solution, as the decomposition itself needs to be approximated (see technical note 7 in chapter 7). A binary variable may, for instance, be estimated by OLS when one thinks that the linear probability model is acceptable. This could be the case for a well-balanced binary variable (that is, not too far from the 50–50 split) for which the probit and logit model specifications are fairly linear. The advantage is that the decomposition of the concentration index would be accurate. Thus, when dealing with a health variable whose ideal specification is nonlinear, one has to decide whether to approximate its model by a linear specification or whether to approximate the decomposition of the concentration index. The alternative consists of estimating a nonlinear model before using ADePT and then decomposing the inequality in

**Table H8c: Elasticities, Linear Model**

	<i>adlhearing</i>	<i>adleyesight</i>	<i>adlwalk</i>
Male	−0.1046	0.0742	0.3792
Age	2.8138	2.1797	2.6384
Pcexp	−0.2851	0.0718	−0.1136

Source: Authors.

**Table H8e: Concentration Index of the Covariates**

	<i>adlhearing</i>	<i>adleyesight</i>	<i>adlwalk</i>
Male	−0.0023	−0.0023	−0.0023
Age	0.0368	0.0368	0.0368
Pcexp	0.3561	0.3561	0.3561

Source: Authors.

the (linear) scores of the latent health variable (see Hosseinpoor and others 2006).

### Interpreting the Results

Our example table H6 shows the decomposition of the concentration index for three health status variables. These are binary variables indicating whether the individual suffers from impairment in activities of daily living with respect to hearing, seeing, and walking. Since we are reading table H6, the underlying model explaining each binary variable is linear and estimated by OLS. The interpretation below relates to hearing impairment only.

Gender and age are used as standardizing variables, and their contribution to income-related inequality in health is, respectively, 0.0002 and 0.1036. That is, hearing impairment is slightly more concentrated among the rich due to gender and significantly more so due to age. Since we have chosen to standardize health according to these variables, their total contribution to income-related inequality in health (0.1038) is deemed justified. This positive contribution means that if hearing problems are correlated with age and gender only, they will show a pro-rich distribution.

Per capita expenditure is used as a control variable in order to avoid age and gender picking up the income effect, which would lead to overstandardizing health. The contribution of this factor to inequality is  $-0.1015$ , which is interesting in itself. Since it is our only control variable, total inequality due to control variables also amounts to  $-0.1015$ . Finally, income-related inequity amounts to  $-0.0583 - 0.1038 = -0.1621$  and favors the rich in the sense that the prevalence of hearing impairment is more concentrated among poorer individuals. Overall inequality appears to be smaller (in absolute terms) than inequity, as part of it is masked by the greater need of richer individuals.

Table H8a shows the estimated coefficients of the linear model along with their standard errors (*se*) and asterisks indicating whether the coefficients are statistically significant for thresholds ranging from 1 to 10 percent. On the one hand, the prevalence of both hearing and walking impairment decreases with per capita expenditure, as the estimated coefficients are negative ( $-1.59\text{E-}06$  and  $-1.16\text{E-}06$ , respectively). On the other hand, the positive coefficient of per capita expenditure in the seeing impairment

model (1.38E-06) indicates that this health problem increases with income.

The number of observations can change from one health variable to the next due to dropping of missing values. In this example, all three models use the same sample of 36,701 observations, as do the decompositions presented in table H6.

Finally, table H8a also shows the adjusted  $R^2$ , which is a measure of goodness of fit. The closer the adjusted  $R^2$  is to 1, the more the model explains the variability in the health variable and, consequently, the more meaningful is the decomposition of the concentration index. The model for hearing impairment explains only 9.22 percent of the variability in this health variable. However, the models for seeing and walking impairment (21.31 and 15.59 percent, respectively) fare significantly better.

Table H8c displays the elasticity of each health variable according to each standardizing and control variable. These are simply computed from the estimated models presented in table H8a and are very important, as they are part of the decompositions displayed in table H6.

Elasticities, however, are only meaningful for continuous variables such as age and per capita expenditure. For instance, in the case of hearing impairment, an increase of 1 percent in age results in an increase of 2.8138 percent in the prevalence of this health problem. By contrast, when per capita expenditure is increased by 1 percent, the prevalence of hearing impairment is reduced by 0.2851 percent. The problem with binary variables such as *male* is that they can only take the values 0 and 1, and thus a percentage increase does not make much sense.

Table H8e presents the concentration indexes of the standardizing and control variables. Since they do not depend on the estimated models and the sample size here is the same for all three decompositions (that is, 36,701, see table H8a), the concentration index is the same for all three health variables. When the health variables contain missing values, dropping them leads to different subsamples and, ultimately, to different values of the concentration index.

Males are slightly more concentrated among the poor, and this variable has a negative concentration index. Older individuals are most often richer individuals, and this variable has a positive concentration index. Finally, the concentration index for per capita expenditure is the Gini coefficient, as observations are ranked according to the same variable.

This amounts to 0.3561 and provides a measure of income inequality in the population analyzed.

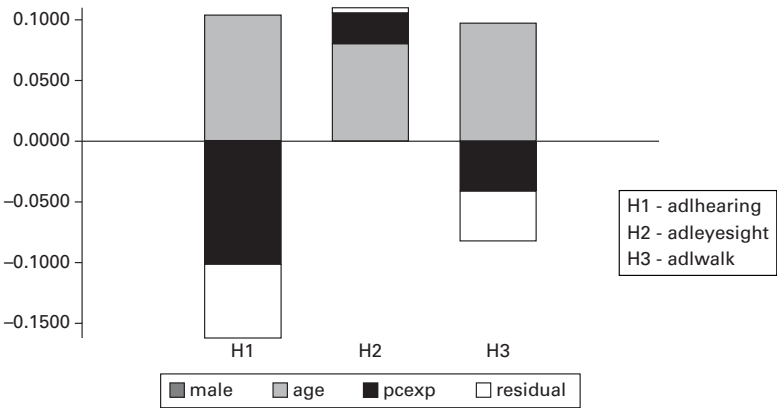
## Decomposition of the Concentration Index

### Concepts

Graphs G7a, G7b, G8a, and G8b all present decompositions of the concentration index of health variables and correspond to tables H6, H7, U6, and U7, respectively. The first two graphs relate to health outcome variables, while the last two relate to health utilization variables. Graphs G7a and G8a display decompositions of the concentration index based on a linear model explaining the health variable, whereas the decompositions shown in graphs G7b and G8b are based on a nonlinear model chosen by ADePT.

These graphs offer a convenient way of showing the respective contributions of the various determinants of health variables to the concentration index. When a determinant is drawn above the horizontal line, this indicates a positive contribution—in other words, the determinant contributes to making the concentration index of the health outcome or use variable more pro-rich. The larger the corresponding area in the graph, the more the determinant is contributing to a pro-rich distribution of the health

**Graph G7a: Decomposition of the Concentration Index for Health Outcomes, Using OLS**



Source: Authors.

outcome or use variable. Symmetrically, when a determinant is drawn below the horizontal line, this indicates a pro-poor contribution. Finally, the contributions of the residuals of the health variable models are also represented on the graphs. This shows the part of the concentration index that is not explained by the determinants.

### **Interpreting the Results**

Our example graph G7a shows the decomposition of the concentration index for three health status variables. These are binary variables indicating whether the individual suffers from impairment in activities of daily living with respect to hearing, seeing, and walking.

Age clearly makes a considerable positive contribution to the concentration index for the three health variables. On the one hand, this means that age makes health impairments more frequent among richer individuals, which partly results from the joint increase in wages and health problems with age. On the other hand, gender makes such a small contribution to the concentration index that it is barely evident on the graph. Per capita expenditure makes the concentration index more pro-poor for hearing and walking impairments. In other words, income makes richer individuals healthier. However, the opposite is true for seeing impairment, which probably results from the more extensive use of this health function by richer individuals.

## **Inequalities in Utilization**

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### **Concepts**

Tables U3–U5 show the distribution of health care utilization by income or any other measure of socioeconomic status. They are similar to tables H3–H5, with the only difference being that they relate to health care utilization instead of health outcomes.

### **Interpreting the Results**

Our example table U3 shows the income-related inequality in the utilization of commune health centers (CHCs), general hospitals, and private

**Table U3: Inequality in Health Care Utilization, Unstandardized**

	<i>CHC</i>	<i>General hospital</i>	<i>Private facility</i>
<b>Quintiles of pexp</b>			
Lowest quintile	0.3832 (0.0161)	0.1578 (0.0113)	0.1610 (0.0106)
2	0.3212 (0.0154)	0.2447 (0.0140)	0.3940 (0.0259)
3	0.3206 (0.0167)	0.3053 (0.0167)	0.4478 (0.0218)
4	0.3064 (0.0196)	0.4865 (0.0256)	0.5251 (0.0231)
Highest quintile	0.1802 (0.0205)	0.7295 (0.0339)	0.7036 (0.0415)
Standard concentration index	-0.1167 (0.0166)	0.3050 (0.0132)	0.2308 (0.0153)
Conc. index with inequality-aversion parameter = 3	-0.1592 (0.0247)	0.4210 (0.0168)	0.3460 (0.0181)
Conc. index with inequality-aversion parameter = 4	-0.1832 (0.0302)	0.4843 (0.0191)	0.4253 (0.0192)
Standard achievement index	0.3376 (0.0084)	0.2674 (0.0075)	0.3433 (0.0098)
Achievement index with inequality-aversion parameter = 3	0.3504 (0.0096)	0.2228 (0.0076)	0.2919 (0.0100)
Achievement index with inequality-aversion parameter = 4	0.3577 (0.0108)	0.1984 (0.0081)	0.2565 (0.0100)

Source: Authors.

Note: standard errors displayed in brackets.

facilities. The corresponding variables measure the number of outpatient visits to these health care providers during a period of one year.

In the case of CHCs, the average number of visits is 0.3832 for the first quintile, and this decreases monotonically with income to 0.1802 for the last quintile. CHC outpatient visits are thus more frequent among the poor. The opposite is true for outpatient visits to general hospitals and private facilities, which increase with income.

The difference in the pattern of utilization between CHCs, on the one hand, and general hospitals and private facilities, on the other, is reflected in their corresponding concentration indexes. The concentration index of CHCs is clearly negative ( $-0.1167$ ), revealing higher utilization by poorer individuals. In contrast, the concentration indexes for visits to general hospitals (0.3050) and private facilities (0.2308) are clearly positive, indicating higher utilization by richer individuals.

When aversion to inequality is higher, the greater weight assigned to the first quintiles renders CHC utilization even more pro-poor (that is, the concentration index becomes more negative), which indicates a greater concentration of utilization among the poor. Utilization of general hospitals and private facilities becomes even more pro-rich (that is, the concentration index increases further), which shows a greater concentration of utilization among the rich. Finally, the achievement index—in other words, the rank-weighted average utilization—of CHCs, general hospitals, and private facilities amounts to 0.3376, 0.2674, and 0.3433, respectively. With higher aversion to inequality, this quantity of utilization increases for CHCs and decreases for general hospitals and private facilities.

## Explaining Inequalities in Utilization

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### Concepts

Tables U6 and U7 show two versions of the decomposition of the health concentration index by determinant of health care utilization. They are similar to tables H6 and H7, with the only difference being that they relate to health care utilization instead of health status. That is why we present only example table U6 here; for more detail, refer to tables H6–H8.

### Interpreting the Results

Our example table U6 shows the decomposition of the concentration index for utilization of CHCs, general hospitals, and private facilities. The corresponding variables measure the number of outpatient visits to these health care providers during a period of one year.

Nine impairments in activities of daily living along with age and gender are used as standardizing variables. These variables are used to account for health care need, and their total contribution of 0.0247 (CHCs), 0.0348 (general hospitals), and 0.0278 (private facilities) to income-related inequality in health care utilization is thus not deemed inequitable. These positive contributions are mostly due to age, which is positively associated with both health care use and income.

**Table U6: Decomposition of the Concentration Index for Utilization Values, Using OLS**

	<i>CHCs</i>	<i>General hospitals</i>	<i>Private facilities</i>
<b>Standardizing (need) variables</b>			
adleyesight	0.0065	0.0086	0.0137
adlhearing	0.0005	0.0004	0.0005
adlmemory	−0.0030	−0.0002	−0.0006
adlconcent	−0.0001	−0.0009	−0.0005
adlunderstand	0.0026	0.0009	0.0009
adlwalk	0.0004	0.0005	−0.0005
adlstairs	−0.0003	−0.0001	0.0007
adl400m	0.0002	0.0012	0.0006
adl10steps	−0.0000	0.0000	−0.0000
male	−0.0008	−0.0005	−0.0007
age	0.0187	0.0250	0.0136
Subtotal	0.0247	0.0348	0.0278
<b>Control variables</b>			
pcexp	−0.1046	0.1177	0.1432
ghe_cap	0.0181	0.0386	0.0429
hi_poor	−0.0822	−0.0407	0.0487
hi_comp	0.0146	0.0600	−0.0556
hi_vol	0.0232	0.0339	−0.0138
Subtotal	−0.1310	0.2095	0.1654
Residual	−0.0104	0.0607	0.0376
Inequality (total)	−0.1167	0.3050	0.2308
Inequity / Unjustified inequality	−0.1414	0.2703	0.2029

Source: Authors.

Per capita expenditure, government health expenditure per capita at the regional level, and three health insurance variables are used as control variables to prevent the need variables from picking up their effect. The total contribution of control factors to inequality amounts to −0.1310, 0.2095, and 0.1654 for CHCs, general hospitals, and private facilities, respectively.

Total inequality can be retrieved by adding the residual to the contributions of standardizing and control variables. Income-related inequity, by contrast, is equal to total inequality less the inequality justified by the inequalities in the standardizing variables:  $-0.1167 - 0.0247 = -0.1414$  for CHCs,  $0.3050 - 0.0348 = 0.2703$  for general hospitals, and  $0.2308 - 0.0278 = 0.2029$  for private facilities. Finally, since need is greater for richer individuals with respect to all three utilization variables (that is, positive contribution of standardizing variables), inequity is less pro-rich (or more pro-poor) than inequality.



## Use of Public Facilities

### Concepts

Table S1 shows how health care utilization is distributed according to per capita total expenditure (or any other welfare aggregate) for various public health services. Its first part presents the average utilization for each quintile of total expenditure as well as the average utilization for the whole population. The same information is then displayed again, but in relative terms—that is, the share of total health care utilization that benefits each quintile. Finally, table S1 also shows the concentration index of each public health service considered. A negative concentration index reveals that poorer individuals use more health care than the rich, whereas a positive value indicates the opposite.

### Interpreting the Results

Our example table S1 presents the utilization of four health services: outpatient visits in CHCs and polyclinics as well as outpatient visits and inpatient admissions to general hospitals. As shown in the sixth line of

**Table S1: Utilization of Public Facilities**

	<i>Outpatient visits (chc)</i>	<i>Outpatient visits (polyclinic)</i>	<i>Outpatient visits (hospital)</i>	<i>Inpatient admissions (hospital)</i>
<b>Means</b>				
Lowest quintile	0.383	0.034	0.158	0.049
2	0.321	0.035	0.245	0.064
3	0.321	0.028	0.305	0.076
4	0.306	0.050	0.486	0.086
Highest quintile	0.180	0.056	0.730	0.096
Total	0.302	0.041	0.385	0.074
<b>Shares</b>				
Lowest quintile	25.3	16.8	8.2	13.2
2	21.3	17.3	12.7	17.1
3	21.2	13.6	15.9	20.4
4	20.3	24.7	25.3	23.3
Highest quintile	11.9	27.5	37.9	26.0
Concentration index	−0.1167	0.1153	0.3050	0.1351

Source: Authors.

table S1, the most frequently used health service is outpatient visits to general hospitals, with 0.385 visit per individual on average. Polyclinics are the least frequently used, with an average of 0.041 outpatient visit, which is even below the average of inpatient admissions to general hospitals (0.074).

There is a very striking contrast between the distribution of outpatient visits to CHCs and the use of general hospital services. The former steadily decreases with income (from an average of 0.383 visit for the first quintile to 0.180 for the last), whereas the latter increases for both inpatient and outpatient care. The relation between income and the use of outpatient services in polyclinics is less well defined, but the use of outpatient services is considerably greater for the last two quintiles.

Table S1 also shows the same pattern in relative terms. For instance, the first quintile alone accounts for 25.3 percent of total outpatient visits to CHCs, and the last quintile accounts for 37.9 percent of outpatient visits to general hospitals.

Finally, these patterns are also reflected in the concentration index. The concentration index of outpatient visits to CHCs is negative ( $-0.1167$ ), which provides an overall measure of the extent to which this health service is distributed in favor of the poor. The concentration index of outpatient visits in general hospitals ( $0.3050$ ) is strongly positive, revealing that richer individuals use this service a lot more than the poor.

## Payments to Public Providers

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### Concepts

Table S2 is very similar to table S1, the only difference being that it relates to health care fees instead of utilization. It shows how health care fees are distributed according to total expenditure per capita (or any other welfare aggregate) for various public health services. Its first part presents the average fee paid by each quintile of total expenditure as well as the average fee paid by the whole population. It then displays the same information in relative terms—that is, the share of total fees paid by each quintile. Finally, it shows the concentration index of each public health service considered. A negative concentration index reveals that poorer individuals contribute more to health care than the rich, whereas a positive value indicates the opposite.

**Table S2: Payments to Public Providers**

	<i>Outpatient visits (chc)</i>	<i>Outpatient visits (polyclinic)</i>	<i>Outpatient visits (hospital)</i>	<i>Inpatient admissions (hospital)</i>
<b>Means</b>				
Lowest quintile	7.41	0.89	11.6	21.1
2	7.00	0.87	27.1	46.4
3	8.12	1.71	38.7	70.7
4	8.85	2.70	77.1	135.2
Highest quintile	4.87	8.08	202.2	261.3
Total	7.25	2.85	71.3	107.0
<b>Shares</b>				
Lowest quintile	20.4	6.2	3.3	3.9
2	19.3	6.1	7.6	8.7
3	22.4	12.0	10.8	13.2
4	24.4	18.9	21.6	25.3
Highest quintile	13.4	56.7	56.7	48.9
	100.0	100.0	100.0	100.0
Concentration index	-0.031	0.480	0.517	0.461

Source: Authors.

## Interpreting the Results

Our example table S2 presents the contributions in thousands of Vietnamese dong made to four health services: outpatient visits to CHCs and polyclinics as well as outpatient visits and inpatient admissions to general hospitals. The sixth line of table S2 shows that inpatient admissions in general hospitals require the highest fees. On average, individuals spend D107,000 on hospital admissions. This average is computed using the whole population, not just patients. Given that in general only a small fraction of the population receives inpatient care, the average fee paid by the patients for this health service is therefore much greater. The whole population also pays D71,300, on average, for outpatient visits in general hospitals and relatively little for outpatient visits in CHCs (D7,325) and polyclinics (D2,850).

There is a striking difference between the distribution of fees paid for outpatient care in CHCs and in the other health services analyzed. The former does not exhibit any well-defined pattern, but it is nonetheless clear that the richest quintile contributes considerably less than the others (D4,870). By contrast, contribution to all other health services increases steadily with income. The last quintile contributes almost 20 times more than the first to outpatient costs. Health care fees clearly

increase with income for outpatient visits to polyclinics, but this matters a bit less considering the relatively lower fees involved. However, if the rich pay more, it is also probably because they use more health care services. That is why this picture should be complemented by a benefit incidence analysis (BIA), which can be performed with ADePT by generating the tables S3–S5.

Table S2 also shows the same pattern in relative terms. For instance, the last quintile alone accounts for more than half of total fees paid for outpatient visits in polyclinics and general hospitals (56.7 percent for both). This share is also very high for hospital admissions (48.9), but low for CHCs (13.4).

On the one hand, the concentration index for fees paid for outpatient visits to CHCs is the only negative one ( $-0.031$ ). This shows that poorer individuals spend more than the rich on this type of health care. On the other hand, the concentration index for each of the three other types of health services amounts to approximately 0.5, which is an extremely positive value. This means that richer individuals spend considerably more than the poor on these health services. Finally, when compared to health care utilization, the distribution of fees is significantly more pro-rich for all four health services considered.

### Health Care Subsidies: Cost Assumptions

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#### Concepts

Tables S3–S5 show how public subsidies are distributed according to income (or any other welfare aggregate) for various health services. The difference between these tables is that the subsidy is computed applying the standard BIA constant cost assumption in table S3, using the proportional cost assumption in table S4, and applying the linear cost assumption in table S5. The choice of the method depends on whether we think that the cost incurred by the government when offering a given health service (that is, the unit cost of publicly provided care) is

- the same for all individuals (table S3),
- proportional to the fees paid by the individuals (table S4), or
- made of a minimum fixed cost that increases at the same rate as the individual fees (table S5).

**Table S3: Health Care Subsidies, Constant Unit Cost Assumption**

	<i>Outpatient visits (chc)</i>	<i>Outpatient visits (polyclinics)</i>	<i>Outpatient visits (hospital)</i>	<i>Inpatient admissions (hospital)</i>	<i>Total subsidies</i>
<b>Average subsidy</b>					
Lowest quintile	7.68	1.97	39.93	76.76	126.34
2	5.95	2.03	56.93	89.28	154.20
3	5.37	1.39	67.86	96.36	170.99
4	4.91	2.34	105.78	92.15	205.19
Highest quintile	3.70	2.23	133.37	87.01	226.30
Total	5.52	1.99	80.77	88.31	176.60
<b>Distribution</b>					
Lowest quintile	27.8	19.8	9.9	17.4	14.3
2	21.6	20.4	14.1	20.2	17.5
3	19.5	13.9	16.8	21.8	19.4
4	17.8	23.5	26.2	20.9	23.2
Highest quintile	13.4	22.4	33.0	19.7	25.6
Total	100.0	100.0	100.0	100.0	100.0
Share in the total subsidy	3.1	1.1	45.7	50.0	100.0
Concentration index	-0.1407	0.0343	0.2471	0.0222	0.1201

Source: Authors.

**Table S4: Health Care Subsidies, Proportional Cost Assumption**

	<i>Outpatient visits (chc)</i>	<i>Outpatient visits (polyclinics)</i>	<i>Outpatient visits (hospital)</i>	<i>Inpatient admissions (hospital)</i>	<i>Total subsidies</i>
<b>Mean subsidy</b>					
1	2.01	0.08	7.85	7.83	17.78
2s	1.90	0.08	18.26	17.24	37.48
3	2.21	0.16	26.14	26.34	54.85
4	2.40	0.25	52.01	50.15	104.82
5	1.32	0.75	136.51	97.08	235.66
Total	1.97	0.27	48.15	39.72	90.11
<b>Shares</b>					
1	20.4	6.2	3.3	3.9	3.9
2	19.3	6.1	7.6	8.7	8.3
3	22.4	12.0	10.9	13.3	12.2
4	24.4	18.9	21.6	25.2	23.3
5	13.4	56.7	56.7	48.9	52.3
Total	100.0	100.0	100.0	100.0	100.0
Share in the total subsidy	2.2	0.3	53.4	44.1	100.0
Concentration index	-0.0306	0.4796	0.5174	0.4610	0.4804

Source: Authors.

This choice directly affects the computation of the subsidy since it amounts to the difference between public cost of care and fees paid by the individual. The first two assumptions are extreme particular cases of the more general third assumption. According to the first assumption, individual

**Table S5: Health Care Subsidies, Constant Unit Subsidy Assumption**

	<i>Outpatient visits (chc)</i>	<i>Outpatient visits (polyclinics)</i>	<i>Outpatient visits (hospital)</i>	<i>Inpatient admissions (hospital)</i>	<i>Total subsidies</i>
<b>Mean subsidy</b>					
1	2.50	0.22	19.73	26.15	48.60
2	2.09	0.23	30.61	34.33	67.27
3	2.09	0.18	38.23	40.30	80.80
4	1.99	0.33	60.87	46.22	109.42
5	1.17	0.37	91.31	51.63	144.48
Total	1.97	0.27	48.15	39.72	90.11
<b>Shares</b>					
1	25.3	16.8	8.2	13.2	10.8
2	21.3	17.3	12.7	17.3	14.9
3	21.2	13.6	15.9	20.3	17.9
4	20.2	24.7	25.3	23.3	24.3
5	11.9	27.5	37.9	26.0	32.1
Total	100.0	100.0	100.0	100.0	100.0
Share in the total subsidy	2.2	0.3	53.4	44.1	100.0
Concentration index	-0.1167	0.1153	0.3050	0.1351	0.2203

Source: Authors.

fees are not used at all when computing the public subsidy. According to the second assumption, the public subsidy is fully determined by the fees. In cases where these two assumptions appear to be too strong, the third assumption provides a convenient intermediary choice. More detail on how the individual subsidy is computed can be found in technical notes 8 to 10 in chapter 7.

The first part of tables S3–S5 displays the average public subsidy received by each income quintile as well as by the whole population. The second part shows the same distribution in relative terms—namely, the share of total public subsidies received by each quintile for each health service analyzed. The share of the total public subsidy for each health service in the total public subsidy is then presented. Finally, these tables show the concentration index of the subsidies. A negative concentration index indicates that poorer individuals benefit more from public financing, whereas a positive value indicates that richer individuals are favored.

## Interpreting the Results

Our example tables present the computed public subsidies (in thousands of Vietnamese dong) for outpatient visits to CHCs and polyclinics as well as outpatient visits and inpatient admissions to general hospitals.

As shown in the first part of table S3, public subsidies generally decrease with income for outpatient visits in CHCs (from D7.68, on average, for the first quintile to D3.70 for the last). However, richer individuals receive more public subsidies for outpatient care in public hospitals, with the highest quintile (133.37) receiving more than three times more than the first (39.93). Public subsidies for outpatient care in polyclinics and inpatient care in general hospitals are only weakly positively related to income.

The same pattern is shown in relative terms in the second part of table S3. For instance, the first quintile alone receives 27.8 percent of the public subsidies associated with outpatient visits in CHCs, while the fifth quintile receives 33 percent of subsidies associated with outpatient care in hospitals. Hospital care receives the bulk of public subsidies. This is split almost evenly between inpatient (50 percent) and outpatient (45.7 percent) care. Outpatient care in CHCs and polyclinics gets only 3.1 and 1.1 percent of total subsidies, respectively.

Finally, concentration indexes show that public subsidies greatly favor the poor in the case of outpatient care in CHCs ( $-0.1407$ ) and favor the rich even more markedly in the case of outpatient care in hospitals ( $0.2471$ ). Outpatient care provided in polyclinics and inpatient care in hospitals are slightly pro-rich. Overall, public subsidies are noticeably pro-rich ( $0.1201$ ) due to the great share and substantial concentration index of outpatient hospital care, which more than offsets the pro-poor distribution of CHC services.

Our example table S4 illustrates that when the proportional cost assumption is made, public subsidies are distributed (in relative terms) the same as health care fees (see technical note 10 in chapter 7 for more details). We thus find that while public subsidies for outpatient care in CHCs tend to decrease slightly with income, all other subsidies have a strong, positive correlation with income. The most striking increase occurs for hospital outpatient care, where the first quintile gets 3.3 percent of the total public subsidy and the fifth quintile gets 56.7 percent. Compared with the standard BIA (table S4), hospital care remains the most subsidized health service, but outpatient care (53.4 percent) receives noticeably more public funding than inpatient care (44.1 percent). This is due to the fact that more fees are collected for outpatient care, and the BIA proportional assumption allocates subsidies with respect to fees. Finally, since health care fees are substantially more concentrated among

the rich, all concentration indexes computed with the BIA proportional assumption are found to be more pro-rich than those computed with the standard BIA assumption.

Our example table S5 illustrates that when the linear cost assumption is made, public subsidies are distributed (in relative terms) the same as health care utilization (see technical note 11 in chapter 7 for more details). This distribution always lies between the ones obtained with the standard BIA assumption (table S3) and the proportional cost assumption (table S4). It is not necessarily always the case, but in our example, the results obtained with the linear cost assumption are closer to those obtained with the standard BIA assumption. All concentration indexes are more pro-rich, and only the subsidies for outpatient care in CHCs remain distributed in favor of the poor. Overall, with a concentration index of 0.2203, total public subsidies are considerably more pro-rich than with the standard BIA assumption.

### **Concentration of Public Health Services**

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#### **Concepts**

Graphs G3–G6 present the concentration curve of the public subsidy for each health service analyzed. Graph G3 relates to the distribution of subsidies computed with the standard BIA method, whereas graphs G4 and G5 describe the distributions of subsidies computed with the proportional and linear cost assumptions, respectively. Finally, graph G6 relates to the distribution of subsidies that were already computed in the data set.

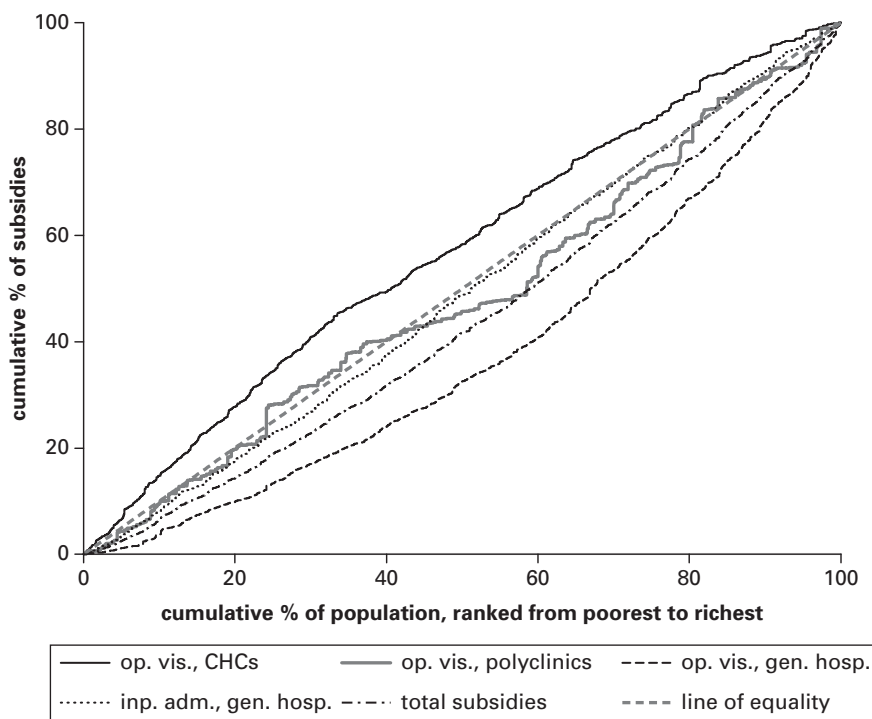
The curves represent the cumulative share of public subsidies according to the cumulative share of population, ranked by increasing consumption. For instance, the poorest 30 percent might benefit from 50 percent of total subsidies. These curves show how public subsidies vary according to consumption: the farther a curve is above the 45° line, the more the corresponding subsidy benefits the poorest households. For some subsidies the concentration curve might lie under the 45° line. In such cases, subsidies are more concentrated among the richest households.

#### **Interpreting the Results**

Example graphs G3–G5 correspond to the subsidies displayed in tables S3–S5 for outpatient care in CHCs and polyclinics and for both outpatient



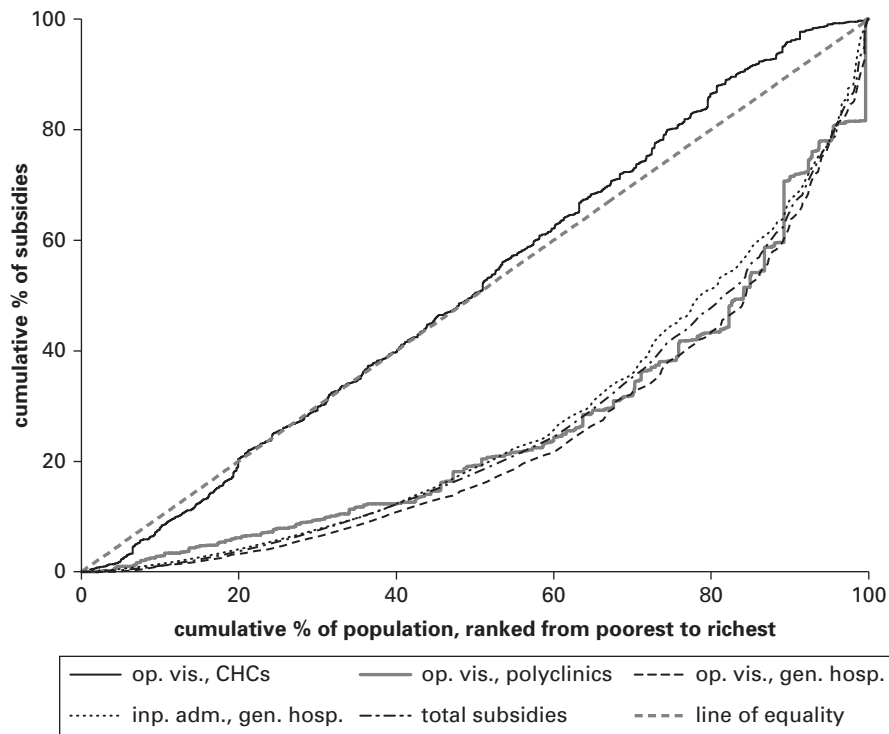
**Graph G3: Concentration Curves of Public Health Care Subsidies,  
Standard BIA**



Source: Authors.

and inpatient care in general hospitals. In graph G3, the concentration curve corresponding to the subsidies granted for outpatient care in CHCs lies above the 45° line. This means that poorer households receive more subsidy than richer ones for this health service, which confirms the pro-poor concentration index ( $-0.1407$ ) found in table S3. The concentration curves related to outpatient care in polyclinics and inpatient care in general hospitals also lie above the 45° line, which is again consistent with the moderately pro-poor concentration indexes found for these health services. In contrast, the concentration curve for outpatient care in general hospitals lies below the 45° line, indicating, as in table S3, that richer households benefit much more from public subsidies for such care. Finally, the concentration curve of total subsidies lies slightly above the 45° line for the first quintile and farther under the line for richer

**Graph G4: Concentration Curves of Public Health Care Subsidies,  
Proportional Cost Assumption**

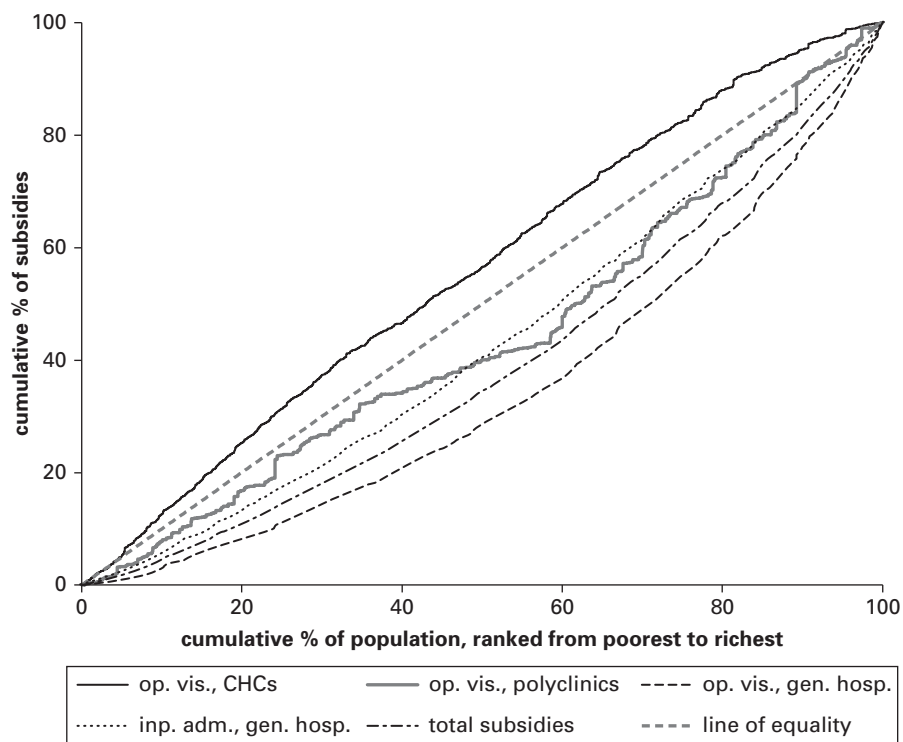


Source: Authors.

households. Overall, the distribution of total public subsidies is thus slightly pro-rich.

Consistent with table S4, graph G4 draws a very different picture of the distribution of public subsidies. In this graph, only the concentration curve for outpatient care in CHCs lies above the 45° line, whereas the concentration curves corresponding to all other health services lie under the line. This confirms that public subsidies computed according to the proportional cost assumption tend to be extremely pro-rich. Finally, graph G5 depicts the intermediate situation displayed in table S5, which occurs when the BIA linear cost assumption is made.

**Graph G5: Concentration Curves of Public Health Care Subsidies, Linear Cost Assumption**



Source: Authors.

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# Technical Notes

These technical notes are intended as a brief guide for users of ADePT Health Outcomes. They are drawn largely (and often with minimal changes) from O'Donnell and others (2008), which provides further information.

## Measuring Inequalities in Outcomes and Utilization

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### Note 1: The Concentration Curve

The concentration curve plots the cumulative percentage of the health sector variable (y axis) against the cumulative percentage of the population, ranked by living standards, beginning with the poorest and ending with the richest (x axis). In other words, it plots shares of the health sector variable against shares of the living standards variable. For example, the concentration curve might show the cumulative percentage of health subsidies accruing to the poorest  $p$  percent of the population. If everyone, irrespective of his or her living standard, has exactly the same value of the health variable, the concentration curve will be a 45° line, running from the bottom left-hand corner to the top right-hand corner. This is known as the line of equality. If, by contrast, the health sector variable takes higher (lower) values among poorer people, the concentration curve will lie above (below) the line of equality. The farther the curve is above the line of equality, the more concentrated the health variable is among the poor.

Concentration curves for the same variable in different countries or time periods can be plotted on the same graph. Similarly, curves for different health sector variables in the same country and time period can be plotted against each other. For example, the analyst may wish to assess whether inpatient care is distributed more unequally than primary care. If the concentration curve for one country (or time period or health service) lies everywhere above that for the other, the first curve is said to dominate the second and the ranking by degree of inequality is unambiguous.<sup>1</sup> Alternatively, curves may cross, in which case neither distribution dominates the other. It is then still possible to compare degrees of inequality, but only by resorting to a summary index of inequality, which inevitably involves the imposition of value judgments concerning the relative weight given to inequality arising at different points in the distribution. The concentration index and the extended concentration index are such summary indexes and are described in the following technical notes.

### **Note 2: The Concentration Index**

Concentration curves (see technical note 1) can be used to identify whether socioeconomic inequality in some health sector variable exists and whether it is more pronounced at one point in time than another or in one country than another. But a concentration curve does not give a measure of the magnitude of inequality that can be compared conveniently across many time periods, countries, regions, or whatever may be chosen for comparison. The concentration index (Kakwani 1977, 1980), which is directly related to the concentration curve, does quantify the degree of socioeconomic-related inequality in a health variable (Wagstaff, van Doorslaer, and Paci 1989; Kakwani, Wagstaff, and van Doorslaer 1997). It has been used, for example, to measure and to compare the degree of socioeconomic-related inequality in child mortality (Wagstaff 2000), child immunization (Gwatkin and others 2003), child malnutrition (Wagstaff, van Doorslaer, and Watanabe 2003), adult health (van Doorslaer and others 1997), health subsidies (O'Donnell and others 2007), and health care utilization (van Doorslaer and others 2006). Many other applications are possible.

The concentration index is defined with reference to the concentration curve (see technical note 1). The concentration index is defined as twice the area between the concentration curve and the line of equality (the 45°

line). If there is no socioeconomic-related inequality, the concentration index is 0. The convention is that the index takes a negative value when the curve lies above the line of equality, indicating a disproportionate concentration of the health variable among the poor, and a positive value when it lies below the line of equality. If the health variable is a “bad,” such as ill health, a negative value of the concentration index means that ill health is higher among the poor. Formally, the concentration index is defined as

$$C = 1 - 2 \int_0^1 L_h(p) dp. \quad (7.1)$$

The index is bounded between  $-1$  and  $1$ . For a discrete living standards variable, it can be written as follows:

$$C = \frac{2}{N\mu_h} \sum_{i=1}^n h_i r_i - 1 - \frac{1}{N}, \quad (7.2)$$

where  $h_i$  is the health sector variable,  $\mu_h$  is its mean, and  $r_i = i/N$  is the fractional rank of individual  $i$  in the living standards distribution, with  $i = 1$  for the poorest and  $i = N$  for the richest.<sup>2</sup> The concentration index depends only on the relationship between the health variable and the rank of the living standards variable and not on the variation in the living standards variable itself. A change in the degree of income inequality need not affect the concentration index measure of income-related health inequality.

The concentration index summarizes information from the concentration curve and can do so only through the imposition of value judgments about the weight given to inequality at different points in the distribution. It is possible to set alternative weighting schemes implying different judgments about attitudes to inequality by using the extended concentration index (see technical note 4). Inevitably, the concentration index loses some of the information that is contained in the concentration curve. The index can be 0 either because the concentration curve lies everywhere on top of the 45° line or because it crosses the line and the (weighted) areas above and below the line cancel out. It is obviously important to distinguish between such cases, and so the summary index should be examined in conjunction with the concentration curve.

The sign of the concentration index indicates the direction of any relationship between the health variable and position in the living standards distribution, and its magnitude reflects both the strength of the relationship and the degree of variability in the health variable. Although this is valuable information, one may also wish to place an intuitive interpretation on

the value of the index. Koolman and van Doorslaer (2004) have shown that multiplying the value of the concentration index by 75 gives the percentage of the health variable that would need to be (linearly) redistributed from the richer half to the poorer half of the population (when health inequality favors the rich) to arrive at a distribution with an index value of 0.

### *Properties of the Concentration Index*

The properties of the concentration index depend on the measurement characteristics of the variable of interest. Strictly, the concentration index is an appropriate measure of socioeconomic-related health (care) inequality when health (care) is measured on a ratio scale with nonnegative values. The concentration index is invariant to multiplication of the health sector variable of interest by any scalar (Kakwani 1980). So, for example, if we are measuring inequality in payments for health care, it does not matter whether payments are measured in local currency or in dollars; the concentration index will be the same. Similarly, it does not matter whether health care is analyzed in terms of utilization per month or if monthly data are multiplied by 12 to give yearly figures. However, the concentration index is not invariant to any linear transformation of the variable of interest. Adding a constant to the variable will change the value of the concentration index. In many applications this does not matter because there is no reason to make an additive transformation of the variable of interest. There is one important application in which this does represent a limitation, however. We are often interested in inequality in a health variable that is not measured on a ratio scale. A ratio scale has a true 0, allowing statements such as “A has twice as much X as B.” That makes sense for dollars or height. But many aspects of health cannot be measured in this way. Measurement of health inequality often relies on self-reported indicators of health. A concentration index cannot be computed directly from such categorical data. Although the ordinal data can be transformed into some cardinal measure and a concentration index can be computed for this (Wagstaff and van Doorslaer 1994; van Doorslaer and Jones 2003), the value of the index will depend on the transformation chosen (Erreygers 2005).<sup>3</sup> In cross-country comparisons, even if all countries adopt the same transformation, their ranking by the concentration index could be sensitive to differences in the means of health that are used in the transformation.



A partial solution to this problem would be to dichotomize the categorical health measure. For example, one could examine how the proportion of individuals reporting poor health varies with living standards. Unfortunately, this introduces another problem. Wagstaff (2005) has demonstrated that the bounds of the concentration index for a dichotomous variable are not  $-1$  and  $1$ ; instead, they depend on the mean of the variable. For large samples, the lower bound is  $\mu - 1$  and the upper bound is  $1 - \mu$ . So the feasible interval of the index shrinks as the mean rises. One should be cautious, therefore, in using the concentration index to compare inequality in, for example, child mortality and immunization rates across countries with substantial differences in the means of these variables. An obvious response is to normalize the concentration index by dividing through by  $1$  minus the mean (Wagstaff 2005). If the health variable of interest takes negative as well as positive values, then its concentration index is not bounded within the range of  $(-1, 1)$ . In the extreme, if the mean of the variable were  $0$ , the concentration index would not be defined.

Finally, Bleichrodt and van Doorslaer (2006) have derived the conditions that must hold for the concentration index (and related measures) to be a measure of socioeconomic-related health inequality consistent with a social welfare function. They argue that one condition—the principle of income-related health transfers—is rather restrictive. Erreygers (2006) has derived an alternative measure of socioeconomic-related health inequality that is consistent with this condition and three others argued to be desirable.

### **Note 3: Sensitivity of the Concentration Index to the Living Standards Measure**

Alternative measures of living standards are often available in practice—consumption, expenditure, wealth index—and it is not always possible to establish a clear advantage of one measure over others. It is therefore important to consider whether the chosen measure of living standards influences the measured degree of socioeconomic-related inequality in the health variable of interest. When the concentration index is used as a summary measure of inequality, the question is whether it is sensitive to the living standards measure.

As noted, the concentration index reflects the relationship between the health variable and living standards rank. It is not influenced by the variance

of the living standards measure. In some circumstances, this may be considered a disadvantage. For example, it means that, for a given relationship between income and health, the concentration index cannot discriminate between the degree of income-related health inequality in one country in which income is distributed very unevenly and that in another country in which the income distribution is very equal. Yet, when one is interested in inequality at a certain place and time, it is reassuring that the differing variances of alternative measures of living standards will not influence the concentration index. However, the concentration index may differ if the ranking of individuals is inconsistent across alternative measures.

Wagstaff and Watanabe (2003) demonstrate that the concentration index will differ across alternative living standards measures if the health variable is correlated with changes in an individual's rank on moving from one measure to another. The difference between two concentration indexes  $C_1$  and  $C_2$ , where the respective concentration index is calculated on the basis of a given ranking ( $r_{1i}$  and  $r_{2i}$ )—for example, consumption and a wealth index—can be computed by means of the following regression:

$$2\sigma_{\Delta r}^2 \left( \frac{h_i}{\mu} \right) = \alpha + \gamma \Delta r_i + \varepsilon_i, \quad (7.3)$$

where  $\Delta r_i = r_{1i} - r_{2i}$  is the reranking that results from changing the measure of socioeconomic status, and  $\sigma_{\Delta r}^2$  is its variance. The ordinary least squares (OLS) estimate of  $\gamma$  provides an estimate of the difference ( $C_1 - C_2$ ). The significance of the difference between indexes can be tested by using the standard error of  $\gamma$ .<sup>4</sup>

In practice, the choice of welfare indicator *can* have a large and significant impact on measured socioeconomic inequalities in a health variable, but it depends on the variable examined (see, for instance, Lindelow 2006). Differences in measured inequality reflect the fact that consumption and the asset index measure different things or at least are different proxies for the same underlying variable of interest. But only in cases in which the difference in rankings between the measures is also correlated with the health variable of interest will the choice of indicator have an important impact on the findings. In cases in which both asset and consumption data are available, analysts are in a position to qualify any analysis of these issues by reference to parallel analysis based on alternative measures. However, data on both consumption and assets are often not

available. In these cases, the potential sensitivity of the findings should be explicitly recognized.

#### Note 4: Extended Concentration Index

The regular concentration index  $C$  is equal to

$$C = \frac{2}{n \cdot \mu} \sum_{i=1}^n h_i R_i - 1, \quad (7.4)$$

where  $n$  is the sample size,  $h_i$  is the indicator of ill health for person  $i$ ,  $\mu$  is the mean level of ill health, and  $R_i$  is the fractional rank in the living standards distribution of the  $i$ th person (Kakwani, Wagstaff, and van Doorslaer 1997). The value judgments implicit in  $C$  are seen most easily when  $C$  is rewritten in an equivalent way as follows:

$$C = 1 - \frac{2}{n \cdot \mu} \sum_{i=1}^n h_i (1 - R_i). \quad (7.5)$$

The quantity  $h_i/n\mu$  is the share of health (or ill health) enjoyed (or suffered) by person  $i$ . This is then weighted in the summation by twice the complement of the person's fractional rank—that is,  $2(1 - R_i)$ . So the poorest person has his or her health share weighted by a number close to 2. The weights decline in a stepwise fashion, reaching a number close to 0 for the richest person. The concentration index is simply 1 minus the sum of these weighted health shares.

The *extended* concentration index can be written as follows:

$$C(v) = 1 - \frac{v}{n \cdot \mu} \sum_{i=1}^n h_i (1 - R_i)^{(v-1)} \quad v > 1. \quad (7.6)$$

In equation 7.6,  $v$  is the inequality-aversion parameter, which is explained below. The weight attached to the  $i$ th person's health share,  $h_i/n\mu$ , is now equal to  $v(1 - R_i)^{(v-1)}$ , rather than by  $2(1 - R_i)$ . When  $v = 2$  the weight is the same as in the regular concentration index; so  $C(2)$  is the standard concentration index. By contrast, when  $v = 1$  everyone's health is weighted equally. This is the case in which the value judgment is that inequalities in health do not matter. So  $C(1) = 0$  however unequally health is distributed across the income distribution. As  $v$  is raised above 1, the weight attached to the health of a very poor person rises, and the weight attached to the health of a person above the 55th percentile decreases. For  $v = 6$ , the weight attached to

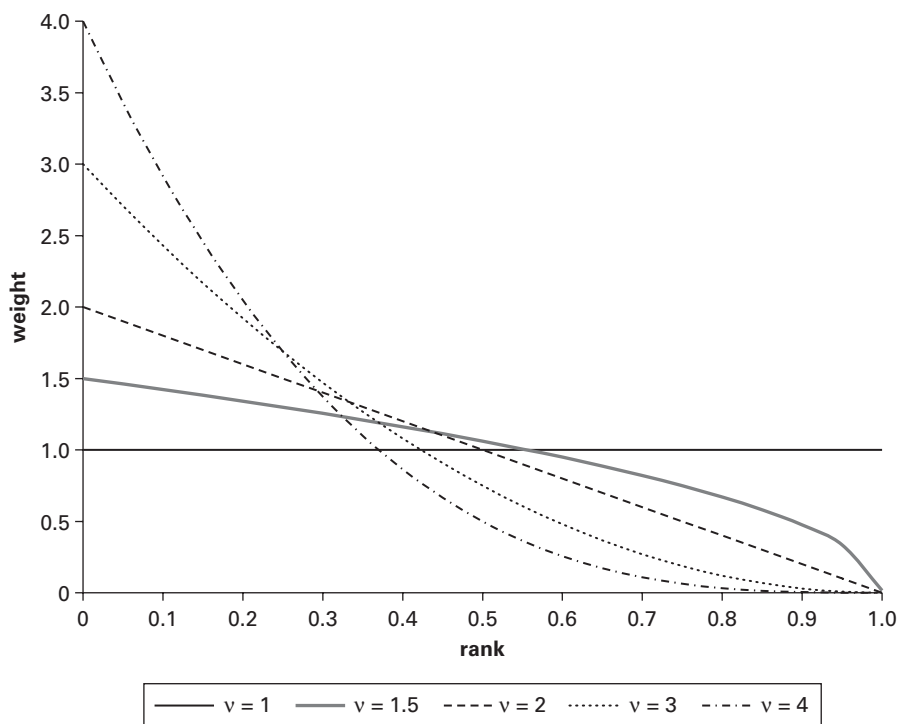
the health of a person in the top two quintiles is virtually 0. When  $v$  is raised to 8, the weight attached to the health of a person in the top *half* of the income distribution is virtually 0 (see figure 7.1).

### Note 5: Achievement Index

The measure of “achievement” proposed in Wagstaff (2002) reflects the average level of health and the inequality in health between the poor and the better off. It is defined as a weighted average of the health levels of the various people in the sample, in which higher weights are attached to poorer people than to better-off people. Thus, achievement might be measured by the following index:

$$I(v) = \frac{1}{n} \sum_{i=1}^n h_i v (1 - R_i)^{(v-1)}, \quad (7.7)$$

**Figure 7.1: Weighting Scheme for Extended Concentration Index**



Source: Wagstaff 2002.

which is a weighted average of health levels, in which the weights are as graphed in the preceding note and average to 1. This index can be shown to be equal to the following (Wagstaff 2002):

$$I(v) = \mu[1 - C(v)]. \quad (7.8)$$

When  $h$  is a measure of ill health (so high values of  $I(v)$  are considered bad) and  $C(v) < 0$  (ill health is higher among the poor), inequality serves to raise the value of  $I(v)$  above the mean, making achievement worse than it would appear if one were to look at just the mean. If ill health declines monotonically with income, the greater is the degree of inequality aversion, and the greater is the wedge between the mean ( $\mu$ ) and the value of the index  $I(v)$ .

## Explaining Inequalities and Measuring Inequity

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### Note 6: Demographic Standardization of Health and Utilization

In the analysis of inequality in health and utilization, the basic aim of standardization is to describe the distribution of health or utilization by living standards conditional on other factors, such as age and sex. This is referred to as the age-sex standardized distribution of health or utilization. It is interesting only if two conditions are satisfied: (a) the standardizing variables are correlated with the living standards, and (b) they are correlated with health or utilization. The purpose is not to build a causal, or structural, model to explain health or utilization. The analysis remains descriptive, but we simply seek a more refined description of the relationship between health or utilization and living standards.

There are two fundamentally different ways of standardizing, direct and indirect. Direct standardization provides the distribution of health or utilization across living standard groups that would be observed if all groups had the same age structure, for example, but had group-specific intercepts and age effects. Indirect standardization, however, “corrects” the actual distribution by comparing it with the distribution that would be observed if all individuals had their own age, but the same mean age effect as the entire population. Although direct standardization requires that individuals be categorized into living standard groups, this is not necessary with the indirect method.

Both methods of standardization can be implemented through regression analysis. In each case, one can standardize for either the full or the partial correlations of the variable of interest with the standardizing variables. In the former case, only the standardizing, or confounding, variables are included in the regression analysis. In the latter case, nonconfounding variables are also included, not to standardize these variables but to estimate the correlation of the confounding variables with health or utilization conditional on these additional variables. For example, take the case in which age is correlated with education and both are correlated with both health or utilization and income. If one includes only age in a health regression, then the estimated coefficient on age will reflect the joint correlations with education and, inadvertently, one would be standardizing for differences in education, in addition to age, by income. One may avoid this, if so desired, by estimating the age correlation conditional on education.

### *Indirect Standardization*

The most natural way to standardize is by the indirect method, which proceeds by estimating a health or utilization regression such as the following:

$$y_i = \alpha + \sum_j \beta_j x_{ji} + \sum_k \gamma_k z_{ki} + \varepsilon_i, \quad (7.9)$$

where  $y_i$  is health or utilization;  $i$  denotes the individual; and  $\alpha$ ,  $\beta$ , and  $\gamma$  are parameter vectors. The  $x_j$  are confounding variables for which we want to standardize (for example, age and sex), and the  $z_k$  are nonconfounding variables for which we do *not* want to standardize but do want to control for in order to estimate partial correlations with the confounding variables. If we want to standardize for the full correlations with the confounding variables, the  $z_k$  variables are left out of the regression. OLS parameter estimates  $(\hat{\alpha}, \hat{\beta}_j, \hat{\gamma}_k)$ , individual values of the confounding variables ( $x_{ji}$ ), and sample means of the nonconfounding variables ( $\bar{z}_k$ ) are then used to obtain the predicted, or “ $x$ -expected,” values of the health indicator  $\hat{y}_i^x$ :

$$\hat{y}_i^x = \hat{\alpha} + \sum_j \hat{\beta}_j x_{ji} + \sum_k \hat{\gamma}_k \bar{z}_k. \quad (7.10)$$

Estimates of indirectly standardized health ( $\hat{y}_i^{IS}$ ) are then given by the difference between actual and  $x$ -expected health or utilization, plus the overall sample mean ( $\bar{y}$ ),

$$\hat{y}_i^{IS} = y_i - \hat{y}_i^X + \bar{y}. \quad (7.11)$$

The distribution of  $\hat{y}_i^{IS}$  (for example, across income) can be interpreted as the distribution of health or utilization that would be expected, irrespective of differences in the distribution of  $x$  across income. A standardized distribution of health or utilization across quintiles could be generated, for instance, by averaging  $\hat{y}_i^{IS}$  within quintiles.

### *Direct Standardization*

The direct method of standardization is more restrictive because it requires grouping health or utilization by categories of living standards. The regression-based variant of direct standardization proceeds by estimating, for each living standard group ( $g$ ), an equation such as the following:

$$y_i = \alpha_g + \sum_j \beta_{jg} x_{ji} + \sum_k \gamma_{kg} z_{ki} + \varepsilon_i, \quad (7.12)$$

which is a group-specific version of equation 7.9. OLS estimates of the group-specific parameters ( $\hat{\alpha}_g, \hat{\beta}_{jg}, \hat{\gamma}_{kg}$ ), sample means of the confounding variables ( $\bar{x}_j$ ), and group-specific means of the nonconfounding variables ( $\bar{z}_{kg}$ ) are then used to generate directly standardized estimates of the health or utilization variable  $\hat{y}_i^{DS}$  as follows:

$$\hat{y}_i^{DS} = \hat{y}_g^{DS} = \hat{\alpha}_g + \sum_j \hat{\beta}_{jg} \bar{x}_j + \sum_k \hat{\gamma}_{kg} \bar{z}_{kg}. \quad (7.13)$$

This method immediately gives the standardized distribution of health or utilization across groups because there is no intragroup variation in the standardized values.

For grouped data, both the direct and indirect methods answer the question, what would the distribution of health or utilization across groups be if there were no correlation between health or utilization and demographics? But their means of controlling for this correlation is different. The direct method uses the demographic distribution of the population as a whole (the  $\bar{x}_j$ ), but the behavior of the groups (as embodied in  $\hat{\beta}_{jg}$  and  $\hat{\gamma}_{kg}$ ). The indirect method employs the group-specific demographic characteristics (the  $\bar{x}_{jg}$ ), but the population-wide demographic effects (in  $\hat{\beta}_j$  and  $\hat{\gamma}_k$ ). The advantage of the indirect method is that it does not require any grouping and is equally feasible at the individual level. The results of the two methods

will differ to the extent that there is heterogeneity in the coefficients of  $x$  variables across groups because the indirect methods impose homogeneity, and the difference will depend on the grouping used in the direct method.

### Note 7: Decomposition of the Concentration Index

For ease of exposition, we refer to any health sector variable, such as health, health care use, or health care payments, as “health” and to any (continuous) measure of socioeconomic status as “income.” Wagstaff, van Doorslaer, and Watanabe (2003) demonstrate that the health concentration index can be decomposed into the contributions of individual factors to income-related health inequality, in which each contribution is the product of the sensitivity of health with respect to that factor and the degree of income-related inequality in that factor. For any linear additive regression model of individual health ( $y_i$ ), such as

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i, \quad (7.14)$$

the concentration index for  $y$  ( $C$ ) can be written as follows:

$$C = \sum_k (\beta_k \bar{x}_k / \mu) C_k + GC_\varepsilon / \mu, \quad (7.15)$$

where  $\mu$  is the mean of  $y$ ,  $\bar{x}_k$  is the mean of  $x_k$ ,  $C_k$  is the concentration index for  $x_k$  (defined analogously to  $C$ ), and  $GC_\varepsilon$  is the generalized concentration index for the error term ( $\varepsilon$ ). Equation 7.15 shows that  $C$  is equal to a weighted sum of the concentration indexes of the  $k$  regressors, where the weight for  $x_k$  is the elasticity of  $y$  with respect to  $x_k$   $\left( \eta_k = \beta_k \frac{\bar{x}_k}{\mu} \right)$ .

The residual component—captured by the last term—reflects the income-related inequality in health that is not explained by systematic variation in the regressors by income, which should approach 0 for a well-specified model.

The decomposition result holds for a linear model of health care. If a nonlinear model is used, then the decomposition is possible only if some linear approximation to the nonlinear model is made. One possibility is to use estimates of the partial effects evaluated at the means (van Doorslaer, Koolman, and Jones 2004). That is, a linear approximation to equation 7.14 is given by



$$y_i = \alpha^m + \sum_j \beta_j^m x_{ji} + \sum_k \gamma_k^m z_{ki} + u_i, \quad (7.16)$$

where the  $\beta_j^m$  and  $\gamma_k^m$  are the partial effects,  $dy/dx_j$  and  $dy/dz_k$ , of each variable treated as fixed parameters and evaluated at sample means, and  $u_i$  is the implied error term, which includes approximation errors. Because equation 7.16 is linearly additive, the decomposition result (Wagstaff, van Doorslaer, and Watanabe 2003) can be applied, such that the concentration index for  $y$  can be written as

$$C = \sum_j (\beta_j^m \bar{x}_j / \mu) C_j + \sum_k (\gamma_k^m \bar{z}_k / \mu) C_k + GC_u / \mu. \quad (7.17)$$

Because the partial effects are evaluated at particular values of the variables (for example, the means), this decomposition is not unique. This is the inevitable price to be paid for the linear approximation.

### Note 8: Distinguishing between Inequality and Inequity

There typically is inequality in the utilization of health care in relation to socioeconomic characteristics, such as income. In high-income countries poorer individuals generally consume more health care resources as a result of their lower health status and greater need for health care. Obviously, such inequality in health care use cannot be interpreted as inequity. In low-income countries, the lack of health insurance and purchasing power among the poor typically means that their utilization of health care is less than that of the better off despite their greater need (Gwatkin 2003; O'Donnell and others 2007). In this case, the inequality in health care use does not fully reflect the inequity. To measure inequity, inequality in utilization of health care must be standardized for differences in need. After standardization, any residual inequality in utilization, by income for example, is interpreted as horizontal inequity, which could be pro-rich or pro-poor. Similarly, income-related inequality in health must also be standardized if we want to assess the extent of inequity that this involves. For instance, both income and health are quite naturally correlated with age. This is generally not deemed inequitable and should thus be taken out of total income-related income inequality to get a measure of horizontal inequity.

As noted in technical note 7, if a health sector variable is specified as a linear function of determinants, then its concentration index can be

decomposed into the contribution of each determinant, computed as the product of the health variable's elasticity with respect to the determinant and the latter's concentration index. This makes it possible to explain socioeconomic-related inequality in health and health care utilization. In fact, the decomposition method allows horizontal inequity in utilization to be both measured and explained in a very convenient way. The concentration index for need-standardized utilization is exactly equal to that which is obtained by subtracting the contributions of all need variables from the unstandardized concentration index (van Doorslaer, Koolman, and Jones 2004). Besides convenience, the advantage of this approach is that it allows the analyst to duck the potentially contentious division of determinants into need ( $x$ ) and control ( $z$ ) variables and so the determination of “justified” and “unjustified,” or inequitable, inequality in health care utilization. The full decomposition results can be presented, and users can choose which factors to treat as  $x$  variables and which to treat as  $z$  variables.

## Benefit Incidence Analysis (BIA)

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### Note 9: Public Health Subsidy in Standard BIA

The service-specific public subsidy received by an individual can be expressed as follows:

$$s_{ki} = q_{ki}c_{kj} - f_{ki}, \quad (7.18)$$

where  $q_{ki}$  indicates the quantity of service  $k$  utilized by individual  $i$ ,  $c_{kj}$  represents the unit cost of providing  $k$  in the region  $j$  where  $i$  resides, and  $f_{ki}$  represents the amount paid for  $k$  by  $i$  (user fee). The total public subsidy received by an individual is as follows:

$$s_i = \sum_k \gamma_k (q_{ki}c_{kj} - f_{ki}), \quad (7.19)$$

where  $\gamma_k$  are scaling factors that standardize utilization recall periods across services. One might standardize on the recall period that applies for the service accounting for the greatest share of the subsidy. For example, where this is inpatient care, reported over a one-year period, then  $\gamma_k = 1$  for inpatient care and, for example,  $\gamma_k = 13$  for services reported over a four-week period.

Some surveys ask the amount paid for each public health service. In this case, the public subsidy can be calculated as in equations 7.18 and 7.19. Alternatively, if the survey gives only the total amount paid for all public health services, then modify equation 7.19 to

$$s_i = \sum_k \delta_k q_{ki} c_{kj} - f_i, \quad (7.19')$$

where  $f_i$  is the payment for all public health care and  $\delta_k$  is a scaling factor that standardizes the recall period for the utilization variables on the recall period that applies to the total payment variable.

There is no assurance that  $S_{ki}$ , estimated either by equation 7.19 or 7.19', will always be positive. The response to this problem is often to replace negative estimates of  $S_{ki}$  by 0 (see, for example, O'Donnell and others 2007, 96). This is not altogether satisfactory, and Wagstaff (2010) argues that the presence of implied negative subsidies actually suggests that the constant cost assumption is unreasonable.

Our ultimate interest is in how subsidies vary with household income. This can be measured using the concentration index, in which a positive value indicates a pro-rich distribution and a negative value indicates a pro-poor distribution (see technical note 2). Moreover, Wagstaff (2011) shows that the concentration index of subsidies to subsector  $k$  ( $CI_{S_k}$ ), can be expressed in terms of the concentration indexes for utilization ( $CI_{q_k}$ ) and fees ( $CI_{F_k}$ ):

$$CI_{S_k} = \frac{C_k}{S_k} CI_{q_k} - \frac{F_k}{S_k} CI_{F_k}, \quad (7.20)$$

where  $S_k$  and  $F_k$  are the sum of aggregate subsidies and fee revenues, respectively. The unit cost for subsector  $k$  ( $C_k$ ) equals the sum of these two aggregates divided by the aggregate number of utilization units of subsector  $k$ :

$$C_k = \frac{S_k + F_k}{\sum_i q_{ki}}. \quad (7.21)$$

According to standard BIA, the concentration index of subsidies is smaller the less concentrated utilization is among the better off. But it is also smaller the *more* concentrated user fees are among the better off. In other words, government spending looks less pro-rich if the better off pay higher fees for a given number of units of utilization. In fact, subsidies could turn

out to be pro-poor if fees are sufficiently disproportionately concentrated among the better off, even if utilization is higher among the better off.

**Note 10: Public Health Subsidy with Proportional Cost Assumption**

The assumption being made in the standard approach to BIA is that each unit of utilization is associated with the same unit cost; the more fees that someone pays for a given unit of utilization, the smaller is the subsidy they receive. The reality may be quite different. It may well be that the better off pay higher fees precisely because they receive more services per unit of utilization; that is, they are charged according to the services they receive, not according to the number of units of utilization. In many (perhaps most) countries, user fees are explicitly linked to the quantity of services rendered, rather than being a flat rate for each unit of utilization (for example, each outpatient visit). Fee schedules also often reflect the cost of the services rendered; for example, higher fees are associated with more expensive drugs and tests. When fees reflect the quantity and costs of services rendered, the better off may well be paying more in fees (if they do pay more) because they get more—or more expensive—tests or drugs for a given outpatient visit or inpatient admission.

An alternative to the standard BIA assumption would be that costs vary across individuals according to the fees paid (Wagstaff 2011). Expressing fees as the product of unit fees and utilization, we have

$$S_{ki} = c_{ki} q_{ki} - f_{ki} q_{ki}, \quad (7.22)$$

where  $q_{ki}$  indicates the quantity of service  $k$  utilized by individual  $i$ ,  $c_{ki}$  represents the unit cost of providing  $k$  to individual  $i$ , and  $f_{ki}$  represents the unit fees paid for  $k$  by  $i$ .

As a first approximation, we could assume that unit fees and unit costs are *proportionate* to one another. Thus,

$$c_{ki} = \alpha_k f_{ki}, \quad (7.23)$$

where we expect  $\alpha_k$  to be larger than 1 given that utilization is subsidized. We have

$$S_{ki} = \alpha_k f_{ki} q_{ki} - f_{ki} q_{ki} = (\alpha_k - 1) f_{ki} q_{ki}. \quad (7.24)$$

The fraction  $(\alpha_k - 1)$  can be computed from aggregate data:

$$\alpha_k - 1 = \frac{S_k}{F_k}, \quad (7.25)$$

where  $S_k$  and  $F_k$  are the sum of aggregate subsidies and fee revenues, respectively. Hence, we have

$$S_{ki} = \frac{S_k}{F_k} f_{ki} q_{ki} = \frac{S_k}{F_k} F_{ki}, \quad (7.26)$$

so that total subsidies received by individual  $i$  are proportional to the fees paid, where the factor of proportionality is simply the ratio of subsidies to fees. Using this method, the estimated value of  $S_{ki}$  is always nonnegative.

Under the proportional cost assumption, the concentration index for subsidies is simply equal to the concentration index for fees:

$$Cl_{S_k} = Cl_{F_k}. \quad (7.27)$$

Thus, in contrast to the standard BIA constant cost assumption, the more concentrated are fees among the better off, the greater is the pro-rich bias in the incidence of government spending.

### **Note 11: Public Health Subsidy with Linear Cost Assumption**

The assumption being made in the standard approach to BIA is that each unit of utilization is associated with the same unit cost; the more fees that individuals pay for a given unit of utilization, the smaller is the subsidy they receive. The reality may be quite different. It may well be that the better off pay higher fees precisely because they receive more services per unit of utilization; that is, they are charged according to the services they receive, not according to the number of units of utilization. In many (perhaps most) countries, user fees are linked explicitly to the quantity of services rendered, rather than being a flat rate for each unit of utilization (for example, each outpatient visit). Fee schedules also often reflect the cost of the services rendered; for example, more expensive drugs and tests are associated with higher fees. When fees reflect the quantity and costs of services rendered, the better off may well be paying more in fees (if they do pay more) because they get more—or more expensive—tests or drugs for a given outpatient visit or inpatient admission.

An alternative to the standard BIA assumption would be that costs vary across individuals according to the fees paid (Wagstaff 2011). Expressing fees as the product of unit fees and utilization, we have

$$S_{ki} = c_{ki}q_{ki} - f_{ki}q_{ki}, \quad (7.28)$$

where  $q_{ki}$  indicates the quantity of service  $k$  utilized by individual  $i$ ,  $c_{ki}$  represents the unit cost of providing  $k$  to individual  $i$ , and  $f_{ki}$  represents the unit fees paid for  $k$  by  $i$ .

As a first approximation, we could assume that unit fees and unit costs are *proportionate* to one another. Thus,

$$c_{ki} = \alpha_k f_{ki}, \quad (7.29)$$

where we expect  $\alpha_k$  to be larger than 1 given that utilization is subsidized. We have

$$S_{ki} = \alpha_k f_{ki}q_{ki} - f_{ki}q_{ki} = (\alpha_k - 1)f_{ki}q_{ki}. \quad (7.30)$$

The fraction  $(\alpha_k - 1)$  can be computed from aggregate data:

$$\alpha_k - 1 = \frac{S_k}{F_k}, \quad (7.31)$$

where  $S_k$  and  $F_k$  are the sum of aggregate subsidies and fee revenues, respectively. Hence, we have

$$S_{ki} = \frac{S_k}{F_k} f_{ki}q_{ki} = \frac{S_k}{F_k} F_{ki}, \quad (7.32)$$

so that total subsidies received by individual  $i$  are proportional to the fees paid, where the factor of proportionality is simply the ratio of subsidies to fees. Using this method, the estimated value of  $S_{ki}$  is always non-negative.

Under the proportional cost assumption, the concentration index for subsidies is simply equal to the concentration index for fees:

$$Cl_{S_k} = Cl_{F_k}. \quad (7.33)$$

Thus, in contrast to the standard BIA constant cost assumption, the more concentrated are fees among the better off, the greater is the pro-rich bias in the incidence of government spending.

## Notes

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1. For an introduction to the concept of dominance, its relation to inequality measurement, and the related concept of stochastic dominance, see Deaton (1997).
2. For large  $N$ , the final term in equation 7.2 approaches 0, and it is often omitted.
3. Erreygers (2005) suggests a couple of alternatives to the concentration index to deal with this problem.
4. This ignores the sampling variability of the left-hand-side estimates.

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## **PART II**

# Health Financing and Financial Protection



## What the ADePT Health Financing Module Does

The Health Financing module of ADePT allows users to analyze financial protection in health. Users are able to analyze the incidence of “catastrophic” out-of-pocket health spending—that is, spending exceeding a certain fraction of total household spending or just its nonfood spending. Users can also compute estimates of impoverishment due to out-of-pocket spending—that is, the effect on the estimated incidence and average depth of poverty associated with including or excluding out-of-pocket health spending from one’s measure of living standards.

ADePT allows users to estimate the progressivity of all sources of health financing, including out-of-pocket spending but also private insurance, social insurance, and taxes. Users can also analyze the effects of health financing on income inequality—that is, the redistributive effect of health finance. ADePT can decompose the redistributive effect into (a) a progressivity component, (b) a horizontal inequity component (households with similar incomes paying different amounts for their health care), and (c) a reranking effect (households moving up or down the income distribution as a result of their health care payments).

ADePT can do quite simple analysis as well as more sophisticated analysis. The more sophisticated features of ADePT are indicated with an asterisk. Users not familiar with the literature may wish to focus initially on sections without an asterisk. Except where stated, the summary in this chapter relies on O’Donnell and others (2008).

## Financial Protection

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Health care finance in low-income countries is still characterized by the dominance of out-of-pocket payments and the relative lack of prepayment mechanisms, such as tax and health insurance. Households without full health insurance coverage face a risk of incurring large expenditures for medical care should they fall ill; this will affect their ability to purchase other goods and services that policy makers consider to be important, such as food and shelter.

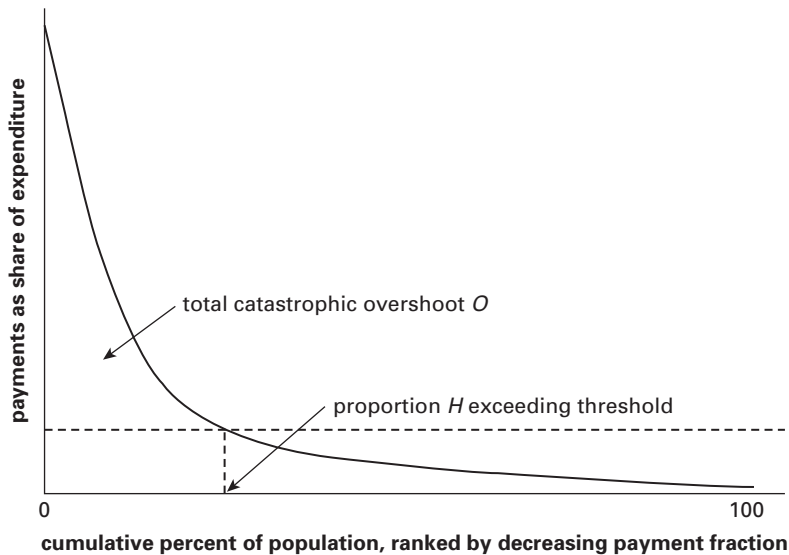
Two approaches have been used to get empirically at this idea. The first looks at payments that are catastrophic in the sense that they involve amounts of money that exceed some fraction of household consumption. The second asks whether the amount of money involved makes the difference between a household being above or being below the poverty line in terms of the money it has available for things other than health care.

### Catastrophic Health Spending

Households are classified as having out-of-pocket health spending that is catastrophic if it exceeds a certain fraction of consumption.<sup>1</sup> The percentage of the population being so classified is likely, of course, to depend on the threshold chosen. ADePT reports the percentage of the population experiencing catastrophic health spending for different thresholds; this is termed “the head count.” ADePT also allows users to plot a chart showing how the head count varies depending on the threshold used, as in figure 8.1.

Policy makers might be concerned not just about the percentage of households exceeding the threshold but also about the amount by which they exceed it. This is analogous to the issue of poverty measurement: policy makers are concerned not just about the percentage of the population that falls below the poverty line but also about how far they fall below it. So, in addition to reporting the incidence of catastrophic health payments, ADePT Health Financing also reports the *intensity* of catastrophic health care payments, through a concept known as “the overshoot”: the larger the amount by which “overshooting” households exceed the threshold, the greater is the (average) overshoot. In figure 8.1, the area below both the

**Figure 8.1: Health Payments Budget Share and Cumulative Percentage of Households Ranked by Decreasing Budget Share**



Source: O'Donnell and others 2008.

curve and the threshold represents the total catastrophic overshoot. The “mean positive overshoot” is simply the average amount of overshoot among households overshooting the threshold.

ADePT also gets at another possible concern of policy makers, namely, they might care more if the households experiencing catastrophic payments are poor than if they are rich. ADePT reports the concentration index for catastrophic payments, in which a negative value means that the households reporting catastrophic payments are largely poor ones. In addition, ADePT reports a weighted head count index that weights the degree to which a household exceeds the threshold by its position in the income distribution; it is the product of the head count and the complement of the concentration index. If the concentration index is negative, the weighted head count exceeds the unweighted head count. A policy maker who is averse to the poor disproportionately experiencing catastrophic payments might want to track the weighted head count rather than the unweighted one. ADePT undertakes the same exercise for the overshoot.

### Poverty and Health Spending

It is common to hear of households being impoverished as a result of large out-of-pocket spending—that is, in the absence of this large out-of-pocket spending, their living standards would have been high enough to keep them above the poverty line.<sup>2</sup> The implicit assumption here is that out-of-pocket spending should not be seen as contributing to the household's living standards: rather, in using the money to purchase health care, the household has sacrificed what would have been purchased in the absence of the health shock that necessitated the health spending. For each household, ADePT compares aggregate consumption including out-of-pocket spending (what the household's consumption would have been in the absence of the health shock) with aggregate consumption *excluding* out-of-pocket spending (what its consumption actually is). If the latter is below the poverty line and the former is above the poverty line, the household is impoverished as a result of the out-of-pocket spending. ADePT compares the poverty head count (the fraction of the population that is poor) with the two definitions of consumption; this allows users to get a sense of how much out-of-pocket spending contributes to the poverty head count.

Health spending could, of course, push a poor household even further into poverty. For each household, therefore, ADePT computes the shortfall in its consumption from the poverty line, again using two definitions of consumption: the first *including* out-of-pocket spending, the second *excluding* out-of-pocket spending. The poverty gap is the aggregate of all shortfalls from the poverty line. ADePT computes this for the two definitions of consumption to get a sense of how much the poverty gap is due to out-of-pocket spending.

### Progressivity and Redistributive Effect

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Catastrophic and impoverishing health payments speak to the issue of financial protection. An equally important issue is the fairness or equity of a country's health financing arrangements. The amount people pay for health care through the various sources of financing—out-of-pocket payments, private insurance, social insurance, and taxes—affects the amount of money they have to spend on things other than health care. Since out-of-pocket payments reflect—at least to a degree—health shocks, they are



typically seen as involuntary. So what people have to spend after paying for health care can be seen as a measure of *discretionary* income. The way a country finances its health care affects the distribution of discretionary income: if the financing system relies on regressive sources of financing (that is, ones that absorb a larger share of a poor household's income than of a rich household's), the health financing system will *increase* inequality in discretionary income; if the system relies on progressive sources, it will *reduce* inequality in discretionary income.

### Progressivity

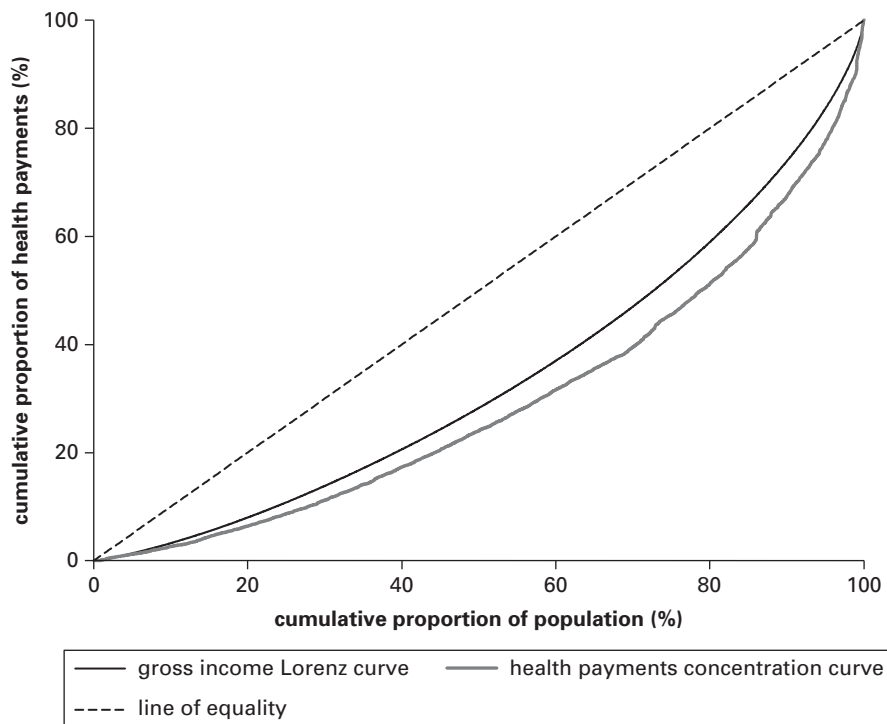
ADePT generates easy-to-understand tables and charts that help policy makers to see how progressive or regressive health care payments are.<sup>3</sup> The basic approach is to see how the share of income paid toward health care varies across income groups—if it rises, health care payments are progressive; if it falls, they are regressive.

ADePT also reports Kakwani's progressivity index, which is based on a comparison of the income distribution (captured by the Lorenz curve) and the distribution of health care payments (captured by the payment concentration curve, which graphs the cumulative share of payments against the cumulative share of households, ranked in ascending order of income). If, as in figure 8.2, the distribution of payments is more unequal than the distribution of income (that is, the payment curve lies below the Lorenz curve), payments are progressive. They are regressive if payments are more equal than income, that is, the payment concentration curve lies *above* the Lorenz curve. The index is equal to twice the area between the two curves, with a positive sign in front of it if payments are progressive. It is equal to the difference between the payment concentration index (twice the area between the payment concentration curve and the line of equality) and the Gini coefficient.

### Redistributive Effect\*

If health care payments are regressive, other things being equal, the distribution of income *before* health care payments is more equal than the distribution of income *after* health care payments—that is, the prepayment Gini

**Figure 8.2: Kakwani's Progressivity Index**



Source: Authors.

coefficient is smaller than the postpayment Gini coefficient.<sup>4</sup> By contrast, if payments are progressive, health care finance exerts an *equalizing* effect on income distribution—that is, the prepayment Gini coefficient is *larger* than the postpayment Gini coefficient. The size of the disequalizing or equalizing effect on income distribution is measured by the difference between the prepayment and postpayment Gini coefficients.

This *redistributive* effect depends on four things:

- The *progressivity of health care payments* as measured by Kakwani's index.
- The *share of income being absorbed by health care payments*. The bigger the share, the greater is the effect on income inequality. Thus, countries' rankings by progressivity do not automatically mirror their rankings by redistributive effect.

- The *degree of horizontal inequity* in health care finance—that is, the degree to which households with a similar ability to pay end up spending similar amounts on health care. The source of inequity could arise in the tax system (the source of income might affect the tax rate), in social insurance contributions (members of one scheme may have a steeper contribution schedule than members of other schemes), in private insurance (risk-rated premiums may translate into the better off facing different premiums), or in out-of-pocket payments (people hit with multiple health problems at a given income level will likely end up paying more). Horizontal inequity is measured with reference to the inequality in postpayment income among groups of prepayment equals and is denoted by HI in equation 8.1. The larger the inequality in postpayment income among each group of prepayment equals, the greater is the degree of horizontal inequity. Each group's inequality in postpayment income is weighted by the product of its population share and its postpayment income share. Horizontal inequity is always nonnegative by construction (the within-group Gini coefficients cannot be negative) and serves to reduce the equalizing effect of health care payments or amplify their disequalizing effect. In other words, horizontal inequity reduces the redistributive effect, defined as the difference between the prepayment and postpayment Gini coefficients.
- The *degree of reranking*—that is, the extent to which households go up or down the distribution of discretionary income as a result of their payments for health care. The World Bank's Voices of the Poor exercise recorded the case of a 26-year-old man in Lao Cai, Vietnam, who, as a result of the large health care costs necessitated by his daughter's severe illness, moved from being the richest man in his community to being one of the poorest. Reranking is measured by the difference between the postpayment Gini coefficient and the postpayment concentration index, obtained by first ranking households by their prepayment income and then, within each group of prepayment income, ranking households by their postpayment income. Reranking also reduces the redistributive effect.

The equation linking these concepts is, roughly speaking,

$$RE = [g/(1 - g)] Kakwani - HI - Reranking, \quad (8.1)$$

where  $RE$  is the Gini coefficient for prepayment income minus the Gini coefficient for postpayment income;  $g$  equals health care payments as a share of prepayment income;  $Kakwani$  is Kakwani's progressivity index (computed on the assumption that households with similar "ability to pay" end up paying the same);  $HI$  is the horizontal inequity index; and  $Reranking$  is the reranking index. ADePT reports each component of this equation for each source of financing as well as for total health care payments.

### Notes

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1. For further details, see technical notes 12–15 in chapter 13; O'Donnell and others (2008, ch. 18).
2. For further details, see technical notes 16–18 in chapter 13; O'Donnell and others (2008, ch. 19).
3. For further details, see technical notes 19–20 in chapter 13; O'Donnell and others (2008, ch. 16).
4. For further details, see technical notes 21–22 in chapter 13; O'Donnell and others (2008, ch. 17). ADePT computes the decomposition terms using the approach outlined in van de Ven, Creedy, and Lambert (2001).

### References

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- O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow. 2008. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.
- van de Ven, J., J. Creedy, and P. J. Lambert. 2001. "Close Equals and Calculation of the Vertical, Horizontal, and Reranking Effects of Taxation." *Oxford Bulletin of Economics and Statistics* 63 (3): 381–94.

# Data Preparation

ADePT has no data manipulation capability. Hence, the data need to be prepared *before* they are loaded into ADePT. This chapter outlines the data needed by ADePT Health Financing for different types of analysis.

The data requirements for the various analyses that ADePT Health Financing can do are summarized in table 9.1. An alternative way of reading the table is to see what analyses are feasible given the data available to ADePT users. ADePT works out what tables and charts can be produced *given the data fields users have completed*: tables and charts that are feasible are shown in black; those that are not feasible are shown in gray. In contrast to the case in the ADePT Health Outcomes module, the data requirements do not increase as the analysis becomes more sophisticated.

## Ability to Pay (Consumption)

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In a developing-country context, given the lack of organized labor markets and the high variability of incomes over time, household consumption (or at least expenditure) is generally considered to be a better measure of welfare and ability to pay than income. *Therefore, in ADePT ability to pay is typically total household consumption.* This should be gross of *all* payments toward health care. Out-of-pocket payments for health care may already be included in the measure of household consumption or expenditure; if not, they need to be added in before *the data are loaded into ADePT*. Indirect taxes are reflected in the consumption aggregate—the price that households pay

**Table 9.1: Data Needed for Different Types of ADePT Health Financing Analysis**

<i>Topic and analysis</i>	<i>Ability to pay (typically consumption)</i>	<i>Out-of-pocket payments</i>	<i>Nonfood consumption</i>	<i>Poverty line</i>	<i>Prepayments for health care</i>	<i>National Health Account data on health financing mix</i>
<i>Financial protection</i>						
Catastrophic payments	✓	✓	✓			
Impoverishment	✓	✓		✓		
<i>Progressivity and redistributive effect</i>						
Progressivity	✓	✓			✓	✓
Redistributive effect*	✓	✓			✓	✓

Source: Authors.

Note: \* = A more advanced type of analysis. Prepayments include private insurance premiums, social insurance contributions, and taxes.

includes any indirect taxes. However, the household's consumption aggregate reflects the resources it has at its disposal *after* the payment of direct taxes, social health insurance contributions, and private insurance premiums. Therefore, *before the data are loaded into ADePT*, the fraction of estimated direct tax payments that go to finance health care as well as social health insurance contributions and private insurance premiums should be added to the consumption aggregate.

## Out-of-Pocket Payments

Out-of-pocket spending should include payments for *all* types of health care included in the National Health Account (NHA). This includes payments to government providers (which should include informal payments if possible) as well as payments to private providers (which should include payments to pharmacies).

Estimates of out-of-pocket payments from survey data are potentially subject to both recall bias and small-sample bias owing to the infrequency with which some health care payments are made. Survey estimates of aggregate payments tend to show substantial discrepancies from production-side estimates, when the latter are available. Whether estimates of the distribution, as opposed to the level, of out-of-pocket payments are biased depends on whether reporting of out-of-pocket payments is related systematically to

ability to pay. Under the possibly strong assumption of no systematic misreporting, survey data can be used to retrieve the distribution of payments, and mismeasurement of the aggregate level can be dealt with by applying a macro weight that gives the best indication of the relative contribution of out-of-pocket payments to total revenues.

## **Nonfood Consumption**

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In the case of low-income countries, it might be more appropriate to define catastrophic payments with respect to health payments as a share of expenditure net of spending on basic necessities, notably food outlays. The latter has been referred to as “nondiscretionary expenditure” or “capacity to pay.” The difficulty lies in the definition of nondiscretionary expenditure. A common approach is to use household expenditure net of food spending as an indicator of living standards.

## **Poverty Line**

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To compute poverty impacts, a poverty line needs to be established. Poverty lines are either relative or absolute.

Relative lines are usually expressed as a percentage of mean or median consumption in the country in question or in a region of countries (for example, the European Union). More common in the developing world are absolute poverty lines. These define poverty in relation to an absolute amount of household expenditure per capita. Many countries have their own (absolute) poverty lines. Some are calculated by taking the cost of reaching subsistence nutritional requirements (for example, 2,100 calories a day) and then adding an allowance for nonfood expenditure (for example, adding the amount spent on nonfood by households achieving a calorific intake of 2,100 calories per person).

Another approach is to use the international “dollar-a-day” poverty line developed by the World Bank but also used widely by the United Nations in tracking poverty. The dollar-a-day poverty line has, in fact, been updated recently to \$1.25 a day. A second line is also used, namely, \$2.00 a day. These are amounts in 2005 prices obtained using 2005 purchasing power parities (PPPs) for private consumption. For other years, the convention is

to deflate (or inflate) the poverty line by applying the local consumer price index (CPI). Suppose, for example, that the country's PPP for private consumption in 2005 is 2.02—that is, 2.02 local currency units to the dollar. Then the \$1.25-a-day poverty line is equivalent to 2.53 currency units a day in 2005. Suppose the available household data refer to 2000, and the CPI (with 2005 = 100) for 2000 is 78.05. Then the \$1.25-a-day poverty line is equivalent to \$1.97 in 2000 prices, that is,  $1.25 \times 2.02 \times 0.7805$ . The 2005 PPP and CPI data are downloadable from the World Bank's data website.<sup>1</sup> ADePT users would do well to check the poverty calculations obtained for consumption gross of out-of-pocket payments with the World Bank's "dollar-a-day" figures for the closest year available; this can be done using the Bank's PovCal tool.<sup>2</sup>

### Prepayments for Health Care

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Evaluation of the progressivity and the redistributive effect of health care financing requires examination of all sources of health sector funding, not simply those payments that are made exclusively for health care. So, in addition to out-of-pocket payments, health insurance contributions, and earmarked health taxes, the distributional burden of all direct and indirect taxes is relevant in cases in which, as is commonly true, some health care is financed from general government revenues. Social insurance contributions should also be considered. One source of revenue—foreign aid—is not relevant because the purpose of the analysis is to evaluate redistribution among the domestic population. Assuming that tax parameters have been set for the repayment of foreign loans, the distributional burden of foreign debt financing on the current generation will be captured through evaluation of the tax distribution. In summary, five main sources of health care finance should be considered: direct taxes, indirect taxes, social insurance, private insurance, and out-of-pocket payments.

Survey data are unlikely to provide complete information on household tax and insurance payments. For example, income tax payments or social insurance contributions may not be explicitly identified, and payments through sales taxes almost certainly are not reported. Various approximation strategies are necessary. For example, direct tax and social insurance schedules can be applied to gross incomes or earnings, and the distribution of the sales tax burden can be estimated by applying product-specific tax rates to



disaggregated data on the pattern of household expenditure. This type of exercise is time-consuming and even in industrial countries is hampered by the lack of relevant data (for example, the availability of net income rather than gross income data).

Progressivity and redistributive effect analyses seek to determine the distribution of the real economic burden of health finance, not simply the distribution of nominal payments. So the incidence of payments—who incurs their real cost—must be established or assumed. For example, employer contributions to health insurance most likely result in lower wages received by employees. The extent to which this is true will depend on labor market conditions—in particular, the elasticities of labor demand and supply. Given that the incidence of taxes depends on market conditions, it cannot be determined through the application of universal rules. However, a fairly conventional set of assumptions is shown in table 9.2.

## NHA Data on Health Financing Mix

ADePT provides users with the option of reweighting the sources of financing using “macro weights”—that is, financing shares as recorded in the NHA table on mix of financing. For example, if the NHA data indicate that 20 percent of health expenditure is financed out of pocket, but the household data reveal that only 10 percent of the computed total comes from out-of-pocket payments, users have the option of scaling the out-of-pocket payments up (and other sources down) to mirror the NHA aggregate figures. Of course, this scales the payments of all households up and down by the same percentage, leaving the progressivity of each source unaffected; all that changes is the progressivity of the total.

**Table 9.2: Common Incidence Assumptions for Prepayments in Progressivity Analysis**

<i>Payment toward health care</i>	<i>Incidence</i>
Personal income and property taxes	Legal taxpayer
Corporate taxes	Shareholder (or labor)
Sales and excise taxes	Consumer
Employer social and private insurance contributions	Employee
Employee social insurance contributions	Employee
Individual private insurance premiums	Consumer

Source: O'Donnell and others 2008.

## Notes

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1. See <http://databank.worldbank.org/ddp/home.do>.
2. See <http://iresearch.worldbank.org/PovcalNet/povcalNet.html>.

## Reference

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O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow. 2008. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.

## Example Data Sets

Two data sets are used in this part of the manual to illustrate the analysis undertaken by ADePT. The analysis of financial protection uses data for Vietnam, and the analysis of progressivity and redistributive effect uses data for the Arab Republic of Egypt.

### Financial Protection: Vietnam

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The tables and graphs relating to catastrophic payments and poverty effects were produced using the 1998 Vietnam Living Standards Survey. The survey design is quite complex, and a detailed description can be found on the Living Standards Measurement Study pages on the World Bank website.<sup>1</sup> In order to get nationally representative estimates, it is crucial to use the weights provided (*wt9*). In addition, proper inference also requires taking regional stratification into account (*reg100*), as well as identifying the communes drawn as a primary sampling unit within the strata (*commune*). There are 5,999 households (*hhw*), the size of which is defined as the number of people living and eating meals together in the same dwelling (*hhsz*).

### Ability to Pay

Ability to pay is measured by household yearly total consumption (*exp*).

### **Out-of-Pocket Payments**

Out-of-pocket payments are measured by medical out-of-pocket payments (net of health insurance reimbursements) during the 12 months prior to the survey (*oop*).

### **Nonfood Consumption**

This is measured by household yearly nonfood consumption (*nonfood1*).

### **Poverty Line**

The poverty line is calculated by taking the cost of reaching subsistence nutritional requirements (for example, 2,100 calories a day) and then adding an allowance for nonfood expenditure (for example, adding the amount spent on nonfood by households achieving a calorific intake of 2,100 calories per person).

## **Progressivity and Redistributive Effect: Egypt**

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All tables and graphs relating to progressivity and redistributive effect were produced with the 1997 Egypt Integrated Household Survey. In order to get nationally representative estimates, it is crucial to use the weights provided (*hh\_weight*). In addition, proper inference also requires taking regional stratification into account (*strata*), as well as identifying the primary sampling unit (*psu*). Each of the 2,419 households is uniquely identified (*hid*), and its size is recorded (*hhsiz*e).

Health care in Egypt is financed from various sources. As is common for developing countries, out-of-pocket payments contribute the greatest share of revenue, 52 percent in this case. The next biggest contribution—one-third—is from general government revenues. Social and private health insurance contribute 7 and 5.5 percent, respectively, and an earmarked health tax on cigarette sales makes up the remaining 3 percent of revenues going toward the provision of health care.

### **Ability to Pay**

Ability to pay is based on household expenditure gross of expenditures on health care whether through out-of-pocket payments or prepayments,

including taxes and social health insurance contributions. Ability to pay is defined as total household expenditure, plus tax payments that go toward financing health care, plus social health insurance contributions, all divided by the square root of household size, an often-used equivalence scale (*HH\_expenditure*).

### Out-of-Pocket Payments

These payments are measured by out-of-pocket medical expenses (*oop*) over the last 12 months.

### Prepayments for Health Care

Prepayment variables recorded in the survey are as follows:

- Direct personal taxes—that is, income, land, housing, and property taxes (*direct\_taxes*)
- Private health insurance premiums (*private\_insurance*).

Prepayment variables estimated from other survey information are as follows:

- Sales and cigarette taxes approximated by applying rates to the corresponding expenditures (*cigarette\_tax*)
- Social health insurance contributions estimated by applying contribution rates to earnings or incomes of covered workers or pensioners (*social\_ins\_contributions*).

### NHA Data on Health Financing Mix

The National Health Account (NHA) shares of total health revenues in Egypt (1994–95) from various sources of finance are given in table 10.1. The table also shows which of the various sources of finance can be allocated, either directly or through estimation, using the survey data. In this example, as in most others, the main difficulty concerns allocation of the 33 percent of all health care finance that flows from general government revenues. Only direct personal and sales taxes, which account for only one-sixth of government revenues, can be allocated down to households. Nonetheless,

**Table 10.1: Financing Assumptions, Egypt Example**

<i>Finance source</i>	<i>Share of total finance (%)</i>	<i>Method of allocation</i>	<i>Macro weights</i>		
			<i>Case 1</i>	<i>Case 2</i>	<i>Case 3</i>
<i>General government revenues</i>	32.98				
Taxes	17.81				
Income, capital gains, and property	0.78	Reported	0.0469	0.0552	0.0108
Corporate	4.83	Ventilated			
Other income, profit, and capital gains	0.62	Ventilated			
Domestic sales of goods and services	4.72	Estimated	0.2829	0.2825	0.0649
Import duties	3.64	Ventilated			
Other	3.22	Ventilated			
Nontax revenues	15.16				
Earmarked cigarette tax	3.00	Estimated	0.0300	0.0300	0.0425
Social insurance	6.67	Estimated	0.0667	0.0667	0.0919
<i>Private insurance</i>	5.57	Reported	0.0557	0.0557	0.0768
<i>Out-of-pocket payments</i>	51.77	Reported	0.5177	0.5177	0.7132
<i>Total</i>	100.00		1.0000	1.0000	1.0000

Source: O'Donnell and others 2008.

Note: "Ventilated" means that unallocated taxes are distributed as the weighted average of financing sources that can be allocated.

it is possible to allocate down to households revenues that account for 72 percent of all health care finance.

### Incidence Assumptions for Health Care Payments

We consider three sets of assumptions about the distribution of unallocated revenues:

- *Case 1.* We assume that unallocated general government revenues are distributed as the weighted average of those taxes that can be allocated. Essentially, this involves inflating the weight given to the taxes that can be allocated. For example, the weight on domestic sales taxes is inflated from its actual value of 0.0472 of all health finance to a value of 0.2829 ( $= [4.72/5.5] \times 0.3298$ ) to reflect the distribution of unallocated revenues.
- *Case 2.* We assume that "other income, profits, and capital gains taxes" are distributed as direct personal taxes and that import duties are distributed as sales taxes. It is assumed that the rest of the unallocated revenues are distributed as the weighted average of the allocated taxes.

- *Case 3.* We assume that unallocated revenues are distributed as the weighted average of all allocated payments (and not just allocated taxes).

## Note

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1. See [www.worldbank.org/lsms](http://www.worldbank.org/lsms).

## Reference

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O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow. 2008. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.





# How to Generate the Tables and Graphs

This chapter explains how to set up ADePT Health Financing so as to generate tables and graphs. The assumption is that the data set has been prepared *before* it is loaded into ADePT. The explanation proceeds with a screen shot of ADePT, with numbers on the screenshot corresponding to the steps outlined.

## Financial Protection

Screenshot 11.1: Financial Protection

**ADePT: Health Financing**

Project Module Tools Help

Datasets Variables | Vietnam 1998 Filter **13**

Variable name	Variable label
hid	
hhsz	Household size
hhw	sample weight
reg10o	samp.strata - SVY commands
commune	commune code PSU-SVY commands <b>1</b>
exp	comp.nominal total exp.
oop	Medical exp.12m drop insurance
nonfood1	comp.nominal nfood exp.
hhsz_new	Created by Zurab
pc_exp	Created by Zurab: = exp / hhsz_old

Search  ☐ Enable only common variables

**Health financing**

**Total consumption\*** **4**  **Household size\*** **2**

Non-food consumption

Poverty line(s) **5**

Number of quantiles  
☒ 5 (quintiles) **6** ☐ 10 (deciles)

Weights and survey settings  
 Household weights **3**

Sources of finance ☐ Use NHA weights

Taxes

Social insurance contributions

Private insurance premiums

Out-of-pocket  **7**

Variables for basic tabulations **8**

Urban

Regions

Health insurance

Custom variable

Characteristics of the HH head

Age

Gender

Education

Economic status

**Health Financing** tables selected:0 / feasible:14 / total:17

- ☐ Original Data Report
- ☐ T1: Sources of finance by household characteristics
- ☐ T2: Sources of finance by individual characteristics
- ☒ **9** Financial protection
  - ☐ TF1: Incidence and intensity of catastrophic health payments
  - ☐ TF2: Incidence and intensity of catastrophic health payments, using nonfood
  - ☐ TF3: Distribution-sensitive catastrophic payments measures
  - ☐ TF4: Distribution-sensitive catastrophic payments measures, using nonfood
  - ☐ TF5: Measures of poverty based on consumption gross and net of spending on health care
  - ☐ GF1: Health payment shares
  - ☐ GF2: Effect of health payments on Pen's Parade of the household consumption
- ☐ Progressivity and redistributive effect
  - ☐ TP1: Average per capita health finance
  - ☐ TP2: Shares of total financing
  - ☐ TP3: Financing budget shares
  - ☐ TP4: Decomposition of redistributive impact of health care financing system
  - ☐ GP1: Concentration curves for health payments, taxes
  - ☐ GP2: Concentration curves for health payments, insurance, out-of-pocket
  - ☐ GP3: Health payment shares by quantiles

For all tables  
☐ Standard errors (slow) **10**  
☐ Frequencies **11**

**14** Generate

Table description and if-condition **ADePT system messages**

Description of the currently selected table

IF-condition **12**

1. Start up ADePT, select the Health Finance module, add a data set (click on the “add” button), and then label it (type a name in the box).  
*Hint 1: If you have used ADePT before, your previous session will be reloaded. You have three options in this case. (1) Continue with the same data set, in which case just keep going. (2) Do the same type of analysis you were doing before, but for a different data set with variables labeled the same. In this case, simply “remove” the data set, “add” your new data set, and continue. All the boxes in which you previously entered information will still include the information. If, while running, ADePT finds that your new data set does not include some of the variables, it will mark them in red in the user interface. (3) Start with a new analysis and a new data set. In this case, simply choose Project -> Reset or hit ctrl-R. Hint 2: You can load several data sets into ADePT at once. The variables you want to analyze will need to exist and be similarly named in both data sets. To facilitate this, check the “Enable only common variables” box; this will cause ADePT to show only the variables that appear in all the data sets you have loaded.*
2. Click on the “variables” tab at the top left corner of the ADePT screen and provide a household size variable.
3. Provide household weights and provide the survey settings when relevant.
4. Enter the name of the household total consumption variable. This variable must be gross of all health care payments. Optionally, specify household total nonfood consumption—this is used in the catastrophic payments analysis.
5. Provide the (per capita) poverty line. It is possible to enter more than one poverty line for multiple analyses with different poverty lines; separate them by a space.
6. Indicate whether the tables should present quintiles or deciles.
7. Enter the household total out-of-pocket payments variable.
8. ADePT also produces basic tabulations of health payments according to other characteristics. Optionally, enter household-level variables in the left column of the corresponding section and various characteristics of the household head in the right column.
9. Select which tables and graphs are to be generated. Relevant figures for catastrophic payments and poverty analysis are tables TF1–TF5 and graphs GF1 and GF2. To obtain basic tabulations of the health payments, select tables T1 and T2 for household-level and household head characteristics.
10. Specify whether the standard error of each indicator is to be produced. This is required for inference but slows down computation.
11. Check the “frequencies” box if you want an additional page in the spreadsheet showing the frequencies (that is, number of cases) used to compute each statistic requested.
12. To produce a table or figure for a *subset of cases*, highlight the relevant table or graph and enter the relevant “if condition” in the “if condition” box. *Hint: Each table or graph can have a different “if condition” assigned to it.*
13. To produce *all* the analysis for just a subset of cases, instead click on the “filter” tab, check the “keep observations if” box, and enter the desired condition.
14. Hit the “generate” button to start the computation and generate the outputs.

## Progressivity and Redistributive Effect

Screenshot 11.2: Progressivity and Redistributive Effect

ADePT: Health Financing

Project Module Tools Help

Datasets Variables | Egypt 1997 Filter 13

Variable name	Variable label
hhid	household id code
hhsize	Household Size
hh_weight	strata weights, 1995 pop.est.
strata	group(hhw)
psu	
HH_expenditure	gross consumption 1
direct_taxes	direct tax
indirect_taxes	indirect tax
cigarette_tax	cigarette tax
social_ins_contributions	social insurance contr

Search  ☐ Enable only common variables

Health financing

Total consumption\* 4 HH\_expenditure Household size\* 2 hhsize

Non-food consumption

Poverty line(s)

Number of quantiles  
☒ 5 (quintiles) 5 ☐ 10 (deciles)

Weights and survey settings  
 Household weights 3 hh\_weight

Sources of finance

☒ Use NHIA weights  
 0.0469 0.2829 0.0300

Taxes direct\_taxes indirect\_taxes cigare

Social insurance contributions social\_ins\_contrib 6 7 0.0667

Private insurance premiums private\_insurance 0.0557

Out-of-pocket oop 0.5177

Variables for basic tabulations 8

Urban

Regions region

Health insurance insured

Custom variable

Characteristics of the HH head

Age

Gender

Education

Economic status

Health Financing tables selected: 0 / feasible: 12 / total: 17

- ☐ Original Data Report
- ☐ T1: Sources of finance by household characteristics
- ☐ T2: Sources of finance by individual characteristics
- ☐ Financial protection
  - ☐ TF1: Incidence and intensity of catastrophic health payments
  - ☐ TF2: Incidence and intensity of catastrophic health payments, using nonfood
  - ☐ TF3: Distribution-sensitive catastrophic payments measures
  - ☐ TF4: Distribution-sensitive catastrophic payments measures, using nonfood
  - ☐ TF5: Measures of poverty based on consumption gross and net of spending on health care
  - ☐ GF1: Health payment shares
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- ☒ Progressivity and redistributive effect 9
  - ☐ TP1: Average per capita health finance
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  - ☐ GP1: Concentration curves for health payments, taxes
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  - ☐ GP3: Health payment shares by quantiles

For all tables

☐ Standard errors (slow) 10

☐ Frequencies 11

14 Generate

Table description and if-condition ADePT system messages

Description of the currently selected table

12 IF-condition

1. Start up ADePT, select the Health Finance module, add a data set (click on the “add” button), and then label it (type a name in the box).  
*Hint 1: If you have used ADePT before, your previous session will be reloaded. You have three options in this case. (1) Continue with the same data set, in which case just keep going. (2) Do the same type of analysis you were doing before, but for a different data set with variables labeled the same. In this case, simply “remove” the data set, “add” your new data set, and continue. All the boxes in which you previously entered information will still include the information. If, while running, ADePT finds that your new data set does not include some of the variables, it will mark them in red in the user interface. (3) Start with a new analysis and a new data set. In this case, simply choose Project -> Reset or hit ctrl-R. Hint 2: You can load several data sets into ADePT at once. The variables you want to analyze will need to exist and be similarly named in both data sets. To facilitate this, check the “enable only common variables” box; this will cause ADePT to show only the variables that appear in all the data sets you have loaded.*
2. Click on the “variables” tab at the top left corner of the ADePT screen and provide a household size variable.
3. Provide household weights and provide the survey settings when relevant.
4. Enter the name of the household total consumption variable. This variable must be gross of all health care payments. Optionally, it is also possible to specify household total nonfood consumption; this is used in the catastrophic payments analysis.
5. Indicate whether the tables should present quintiles or deciles.
6. Enter the variable names for taxes, social health insurance contributions, private health insurance premiums, and out-of pocket payments. It is possible to specify more than one tax; separate them by a space.
7. Check the “use NHA weights” box if National Health Accounts (NHA) weights are to be used in aggregating across payment categories and enter NHA weights as fractions. Multiple weights can be used when there are multiple taxes, but they need to be entered in the same order as the tax variables.
8. ADePT also produces basic tabulations of health payments according to other characteristics. Optionally, enter household-level variables in the left column of the corresponding section and various characteristics of the household head in the right column.
9. Select which tables and graphs are to be generated. The relevant figures for progressivity and redistributive effect analysis are tables TP1–TP4 and graphs GP1–GP3. To obtain basic tabulations of health payments, select tables T1 and T2 for household-level and household head characteristics.
10. Specify whether the standard error of each indicator is to be produced. This is required for inference but slows down computation.
11. Check the “frequencies” box if you want an additional page in the spreadsheet showing the frequencies (that is, number of cases) used to compute each statistic requested.
12. To produce a table or figure for a *subset of cases*, highlight the relevant table or graph and enter the relevant “if condition” in the “if condition” box. *Hint: Each table or graph can have a different “if condition” assigned to it.*
13. To produce *all* the analysis for just a subset of cases, instead click on the “filter” tab, check the “keep observations if” box, and enter the desired condition.
14. Hit the “generate” button to start the computation and generate the outputs.



# Interpreting the Tables and Graphs

As detailed in chapter 10, the tables and graphs for the analysis of financial protection were produced using data from the 2006 Vietnam Household Living Standards Survey, while those for the analysis of progressivity and redistributive effect were produced using data from the 1997 Integrated Household Survey for the Arab Republic of Egypt.

## Original Data Report

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### Concepts

The original data report gives basic statistics on the variables provided by users and shows in parentheses the field in which each variable was entered. When users enter National Health Account (NHA) weights, the sources of financing are rescaled to be consistent with their corresponding NHA aggregate. The rescaled sources of financing appear directly below the raw version of them. This report is important, as it makes it possible to detect many of the bold errors that may occur when preparing the data. For each variable, the first column shows the number of observations with a valid value (that is, those that are not represented by a missing value in Stata). The next three columns present the mean, minimum, and maximum values of each variable. Column “p1” gives the first percentile or, in other words, the value that is greater than 1 percent of the values taken by

### Original Data Report

	<i>N</i>	<i>mean</i>	<i>min</i>	<i>max</i>	<i>p1</i>	<i>p50</i>	<i>p99</i>	<i>N_unique</i>
<b>Egypt 1997</b>								
hhsize (Household size)	2,419	1.0	1.0	1.0	1.0	1.0	1.0	1
HH_expenditure (Total consumption)	2,419	6,886	504.6	100,956	1,503	5,567	26,334	2,418
hh_weight (Household weights)	2,419	1.0	0.8	1.5	0.8	0.9	1.5	5
direct_taxes	2,419	15.7	0.0	3,742	0.0	0.0	312	318
rescaled (Tax 1)	2,419	23.6	0.0	5,613	0.0	0.0	468	318
indirect_taxes	2,419	313	3.5	9,507	20.2	169	2,293	2,418
rescaled (Tax 2)	2,419	142	1.6	4,305	9.1	76.6	1,038	2,418
cigarette_tax	2,419	9.6	0.0	2,124	0.0	0.0	51.5	228
rescaled (Tax 3)	2,419	15.5	0.0	3,439	0.0	0.0	83.4	228
social_ins_contrib	2,419	28.4	0.0	765	0.0	6.2	186	987
rescaled (Social insurance contributions)	2,419	34.0	0.0	916	0.0	7.5	223	987
private_insurance	2,419	2.8	0.0	234	0.0	0.0	42.4	237
rescaled (Private insurance premiums)	2,419	29.2	0.0	2,474	0.0	0.0	449	237
oop	2,419	140	0.0	19,233	0.0	42.4	1,443	483
rescaled (Out-of-pocket)	2,419	274	0.0	37,675	0.0	83.1	2,827	483
region (Regions)	2,419	2.6	1.0	5.0	1.0	2.0	5.0	5
insured (Health insurance)	2,419	0.2	0.0	1.0	0.0	0.0	1.0	2
generated (Per capita consumption, gross)	2,419	6,886	505	100,955	1,504	5,567	26,336	2,418
generated (Per capita consumption, net)	2,419	6,367	400	100,712	1,381	5,191	23,376	2,418

the variable (and thus smaller than 99 percent of its values). Column “p50” represents the median, and “p99” represents the 99th percentile. The last column indicates the number of different values taken by each variable.

### Interpreting the Results

Provided that they have been adequately prepared, the identification (ID) variables generally give the number of observations in the sample analyzed, which amounts to 2,419 in our example table. The out-of-pocket expenditures variable (*oop*) also has 2,419 observations and thus does not contain any missing values. Mean out-of-pocket expenditure amounts to LE 140 (Egyptian pounds) and ranges from LE 0 to LE 19,233. The median (LE 42.4) is smaller than the mean, which indicates the expected right-skewed distribution of health expenditure variables. The last column of the table usually makes it possible to identify categorical data. For instance, the variables “region” and “insured,” respectively, take five and two different values.



## Basic Tabulations

### Concepts

Compared with ADePT's original data report, which provides basic summary statistics on all variables specified, tables 1 and 2 provide more in-depth descriptive analysis of the variables related to sources of financing. These tables show the mean financing according to household (table 1) and individual (table 2) characteristics. ADePT also computes standard errors, which are presented in parentheses below their corresponding means. Under the assumption of normal distribution, subtracting twice the standard error from the mean, and then adding twice the standard error to the mean, yields the 95 percent confidence interval. This interval, which is reported in many standard Stata outputs, has a 95 percent chance of containing the true (and unknown) value of interest.

### Interpreting the Results

Both tables are read in the same way. We show here only one example, table 1, which presents the relation between health financing and household

**Table 1: Sources of Finance by Household Characteristics**

	<i>Per capita consumption gross</i>	<i>Direct tax</i>	<i>Indirect tax</i>	<i>Cigarette tax</i>	<i>Social insurance contr.</i>	<i>Private insurance premiums</i>	<i>Out-of- pocket payments</i>	<i>Total payments</i>	<i>Per capita consumption net of payments</i>
<b>Region</b>									
1	6,571 (324)	8.4 (2.0)	79.3 (6.0)	11.3 (1.1)	16.4 (2.3)	24.0 (6.5)	185.9 (30.4)	325.3 (38.7)	6,246 (299)
2	6,269 (234)	16.0 (2.6)	88.8 (6.3)	10.3 (0.8)	24.4 (2.2)	22.2 (5.9)	239.3 (30.7)	401.0 (39.6)	5,868 (219)
3	6,409 (380)	31.0 (16.5)	150.9 (19.0)	14.0 (1.2)	38.5 (4.6)	13.7 (6.2)	320.6 (48.7)	568.7 (63.4)	5,840 (354)
4	8,876 (646)	40.9 (14.8)	223.0 (24.2)	25.9 (10.0)	59.0 (7.2)	54.6 (9.8)	361.9 (118.6)	765.2 (132.6)	8,110 (546)
5	6,983 (546)	39.2 (11.9)	258.2 (40.6)	23.4 (7.7)	52.7 (5.8)	40.4 (13.5)	358.0 (91.5)	771.9 (108.7)	6,211 (482)
<b>Household with private insurance</b>									
no	6,631 (206)	24.2 (4.8)	145.0 (11.6)	13.0 (0.6)	29.9 (2.2)	0.0 (0.0)	284.5 (34.2)	496.6 (40.2)	6,134 (180)
yes	8,206 (354)	33.4 (11.0)	204.9 (17.3)	31.1 (12.1)	64.8 (4.1)	151.6 (15.3)	300.0 (40.3)	785.8 (56.2)	7,420 (320)

Source: Author.

Note: Numbers in parentheses are standard errors.

characteristics. There are two household characteristics: the region of the place of residence (five categories) and whether the household has private health insurance or not (binary variable).

For instance, with LE 8,876 gross consumption per capita, the fourth region is substantially (and statistically significantly) richer than the other regions. All financing sources are also the greatest in this region, but not always statistically significantly so. Households having private health insurance are also significantly richer (LE 8,206) than the uninsured ones (LE 6,631).

## Financial Protection

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### Concepts

Tables F1 and F2 provide information on catastrophic health payments per quintile of gross income. The only difference between the two tables is that the former defines household ability to pay as the sum of all expenditures, whereas the latter defines it as the sum of nonfood expenditures. All measures presented are based on the proportion of health payments in the household budget. The columns give different thresholds above which health payment budget shares might be deemed catastrophic.

The first section of the tables displays the catastrophic payment head count ( $H$ ), which represents the proportion of households with a health payment budget share greater than the given thresholds. This measure provides a simple way of assessing the incidence of catastrophic payments. The second section of the tables presents the catastrophic payment overshoot ( $O$ ), which shows the extent to which, on average, the household health payment budget share exceeds various thresholds. The overshoot is an average taken over all households in the quintile of gross income, irrespective of their health payments. The information displayed in the last section is the mean positive overshoot ( $MPO$ ), which measures the intensity of catastrophic payments—that is, the average excess of health payment budget share of those households with catastrophic payments. Mean positive overshoot is thus the average payment excess, computed for the subsample of households with catastrophic payments in their quintile of gross income. Finally, a standard error is displayed in parentheses below each estimate.

**Table F1: Incidence and Intensity of Catastrophic Health Payments**

	<i>Threshold budget share</i>				
	<i>5%</i>	<i>10%</i>	<i>15%</i>	<i>25%</i>	<i>40%</i>
<b>Head count (H)</b>					
Lowest quintile	33.8 (2.23)	13.6 (1.53)	6.1 (0.96)	1.2 (0.37)	0.0 (0.00)
2	34.9 (1.92)	14.2 (1.17)	7.4 (0.93)	1.4 (0.40)	0.1 (0.13)
3	37.9 (1.86)	16.2 (1.20)	9.0 (0.87)	2.7 (0.53)	0.5 (0.20)
4	33.8 (1.82)	17.1 (1.38)	10.0 (1.01)	4.3 (0.66)	1.2 (0.38)
Highest quintile	28.3 (1.41)	14.5 (0.93)	9.9 (0.82)	4.9 (0.62)	2.1 (0.43)
Total	33.8 (1.03)	15.1 (0.66)	8.5 (0.47)	2.9 (0.25)	0.8 (0.12)
<b>Overshoot (O)</b>					
Lowest quintile	1.9 (0.19)	0.8 (0.12)	0.4 (0.07)	0.1 (0.02)	0.0 (0.00)
2	2.2 (0.18)	1.0 (0.13)	0.5 (0.09)	0.1 (0.04)	0.0 (0.01)
3	2.6 (0.19)	1.4 (0.14)	0.7 (0.11)	0.2 (0.06)	0.0 (0.02)
4	2.9 (0.25)	1.7 (0.20)	1.1 (0.15)	0.4 (0.09)	0.1 (0.04)
Highest quintile	3.0 (0.24)	2.0 (0.21)	1.4 (0.17)	0.7 (0.12)	0.2 (0.06)
Total	2.5 (0.11)	1.4 (0.08)	0.8 (0.06)	0.3 (0.03)	0.1 (0.01)
<b>Mean positive overshoot (MPO)</b>					
Lowest quintile	5.7 (0.35)	6.2 (0.54)	5.9 (0.75)	5.1 (0.67)	
2	6.2 (0.38)	7.1 (0.60)	6.3 (0.76)	7.2 (1.95)	7.6 (0.00)
3	7.0 (0.41)	8.5 (0.64)	8.4 (0.91)	8.4 (1.58)	8.2 (3.04)
4	8.7 (0.56)	10.1 (0.78)	10.9 (0.99)	9.8 (1.43)	6.5 (1.95)
Highest quintile	10.6 (0.72)	13.8 (1.03)	14.1 (1.26)	14.5 (1.51)	9.8 (1.74)
Total	7.5 (0.23)	9.2 (0.35)	9.6 (0.49)	10.5 (0.75)	8.5 (1.23)

Source: Author.

## Interpreting the Results

Our example table F1 shows that when the threshold is raised from 10 to 25 percent of total expenditure, the incidence of catastrophic payments in the lowest quintile of gross income falls from 13.6 to 1.2 percent, and

**Table F2: Incidence and Intensity of Catastrophic Health Payments, Using Nonfood**

	<i>Threshold budget share</i>				
	<i>5%</i>	<i>10%</i>	<i>15%</i>	<i>25%</i>	<i>40%</i>
<b>Head count (H)</b>					
Lowest quintile	72.7 (2.73)	53.8 (2.73)	38.1 (2.26)	19.7 (1.83)	7.1 (1.06)
2	72.9 (1.85)	49.9 (1.90)	35.2 (1.92)	16.9 (1.31)	5.9 (0.85)
3	67.5 (1.75)	46.4 (1.77)	33.3 (1.69)	16.0 (1.19)	6.1 (0.72)
4	59.8 (2.06)	38.1 (1.87)	26.2 (1.75)	14.8 (1.31)	7.3 (0.90)
Highest quintile	42.2 (1.52)	26.7 (1.34)	18.4 (1.13)	10.8 (0.87)	5.4 (0.64)
Total	63.0 (1.18)	43.0 (1.22)	30.2 (1.06)	15.6 (0.72)	6.3 (0.46)
<b>Overshoot (O)</b>					
Lowest quintile	10.9 (0.72)	7.8 (0.62)	5.5 (0.52)	2.8 (0.35)	0.9 (0.15)
2	9.8 (0.50)	6.8 (0.44)	4.6 (0.37)	2.2 (0.25)	0.6 (0.11)
3	9.6 (0.45)	6.8 (0.39)	4.8 (0.33)	2.4 (0.23)	0.8 (0.13)
4	8.4 (0.55)	6.1 (0.48)	4.5 (0.41)	2.5 (0.30)	1.0 (0.16)
Highest quintile	6.2 (0.39)	4.5 (0.34)	3.4 (0.30)	2.0 (0.23)	0.9 (0.14)
Total	9.0 (0.31)	6.4 (0.26)	4.6 (0.22)	2.4 (0.15)	0.8 (0.07)
<b>Mean positive overshoot (MPO)</b>					
Lowest quintile	15.0 (0.73)	14.5 (0.72)	14.4 (0.81)	14.0 (0.96)	12.1 (1.01)
2	13.4 (0.56)	13.5 (0.65)	13.2 (0.74)	12.8 (0.93)	10.1 (1.11)
3	14.2 (0.53)	14.6 (0.65)	14.4 (0.70)	15.0 (1.01)	12.9 (1.47)
4	14.1 (0.71)	16.0 (0.87)	17.2 (1.02)	17.3 (1.15)	13.5 (1.39)
Highest quintile	14.6 (0.79)	16.9 (1.02)	18.6 (1.21)	18.8 (1.39)	16.9 (1.39)
Total	14.2 (0.36)	14.8 (0.38)	15.1 (0.43)	15.2 (0.50)	13.0 (0.56)

*Source:* Author.

the mean overshoot drops from 0.8 percent of expenditure to only 0.1 percent. Unlike the head count and the overshoot, the mean overshoot among those exceeding the threshold need not decline as the threshold is raised. Those in the lowest quintile of income spending more than 10 percent of total expenditure on health care spent, on average, 16.2 percent

(10 percent + 6.2 percent), while those spending more than 25 percent on health care spent 30.1 percent (25 percent + 5.1 percent). No mean positive overshoot is displayed for the 40 percent threshold in the lowest income quintile because no catastrophic payments are observed in this case (that is,  $H = 0$ ). Overall, both the incidence and intensity of catastrophic payments increase with income. The reason is that richer households can spend a larger budget share on health care without having to cut spending on basic necessities.

Finally, for a given threshold and gross income quintile, both the head count and the overshoot are higher, as they must be, when catastrophic payments are defined with respect to health payments relative to nonfood expenditure (see table F2). Another difference is that, in table F2, the incidence of catastrophic payments decreases with income net of food expenditure. In other words, poorer households cut proportionally more nonfood expenditures to cope with health outlays.

## **Distribution-Sensitive Measures of Catastrophic Payments**

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### **Concepts**

Tables F3 and F4 relate catastrophic payment head count and overshoot to household income distribution. As in tables F1 and F2, each column represents a threshold above which household health payments might be considered catastrophic. The first line of these tables shows the concentration index of the incidence of catastrophic payments ( $C_E$ ). A positive value of  $C_E$  indicates a greater tendency for the better off to exceed the payment threshold, whereas a negative value indicates a greater tendency for the worse off to exceed it. The concentration index of payment overshoot ( $C_O$ ) is a very similar measure. This indicates whether the average payment exceeding the threshold is greater among the better off ( $C_O > 0$ ) or among the poor ( $C_O < 0$ ).  $H_W$  and  $H_O$  adjust the catastrophic payment head count ( $H$ ) and overshoot ( $O$ ), respectively, in order to make these measures sensitive to the distribution of income. For instance, when catastrophic payments are more frequent among the poor,  $H_W$  is greater than  $H$  since, according to a social welfare perspective, such catastrophic payments are worse than if they were not at all related to income.

**Table F3: Distribution-Sensitive Catastrophic Payments Measures**

	<i>Threshold budget share</i>				
	5%	10%	15%	25%	40%
Concentration index, C_E	−0.031 (0.015)	0.023 (0.022)	0.092 (0.029)	0.283 (0.044)	0.566 (0.057)
Rank-weighted head count, H_W	34.788 (1.2585)	14.758 (0.7995)	7.698 (0.5565)	2.068 (0.2423)	0.339 (0.0701)
Concentration index, C_O	0.091 (0.023)	0.175 (0.030)	0.270 (0.036)	0.441 (0.048)	0.621 (0.076)
Rank-weighted overshoot, O_W	2.298 (0.1162)	1.144 (0.0776)	0.593 (0.0499)	0.169 (0.0224)	0.025 (0.0067)

Source: Author.

**Table F4: Distribution-Sensitive Catastrophic Payments Measures, Using Nonfood**

	<i>Threshold budget share</i>				
	5%	10%	15%	25%	40%
Concentration index, C_E	−0.100 (0.010)	−0.129 (0.013)	−0.135 (0.016)	−0.113 (0.023)	−0.033 (0.036)
Rank-weighted head count, H_W	69.336 (1.4569)	48.539 (1.5202)	34.339 (1.3077)	17.405 (0.9355)	6.543 (0.5931)
Concentration index, C_O	−0.104 (0.017)	−0.098 (0.020)	−0.083 (0.024)	−0.045 (0.032)	0.036 (0.045)
Rank-weighted overshoot, O_W	9.896 (0.3923)	7.007 (0.3343)	4.950 (0.2763)	2.490 (0.1836)	0.794 (0.0835)

Source: Author.

## Interpreting the Results

In the example tables F3 and F4, it is very clear that the distribution of catastrophic payments depends on whether health payments are expressed as a share of total expenditure or a share of nonfood expenditure. In the former case, catastrophic payments rise with total expenditure, with the only exception being the head count at the 5 percent threshold. As a result, the rank-weighted head count and overshoot are smaller than the unweighted indexes given in tables F1 and F2. But when health payments are assessed relative to nonfood expenditure, the concentration indexes are negative (with only one exception), indicating that the households with low nonfood expenditures are more likely to incur catastrophic payments. As a consequence, the weighted indexes are larger than the unweighted indexes in tables F1 and F2.

## Measures of Poverty Based on Consumption

### Concepts

Table F5 presents poverty measures corresponding to household expenditure both gross and net of health payments. A standard error is displayed in parentheses below each estimate. Even though caution has to be observed (see technical note 18 in chapter 13), comparison of gross and net measures is indicative of the scale of impoverishment due to health payments. The first line of the table shows the poverty head count, which represents the proportion of individuals living below the poverty line. The poverty gap gives the average deficit to reach the poverty line in the population. The normalized poverty gap is obtained by simply dividing the poverty gap by the poverty line. It is useful when making comparisons across countries with different poverty lines and currency units. Finally, the normalized mean positive poverty gap is a measure of poverty intensity—that is, the average poverty gap of the poor divided by the poverty line.

**Table F5: Measures of Poverty Based on Consumption Gross and Net of Spending on Health Care**

	<i>Gross of health payments</i>	<i>Net of health payments</i>
<b>Poverty line = 941.8</b>		
Poverty head count	3.3 (0.52)	4.2 (0.60)
Poverty gap	4.9 (1.03)	6.6 (1.19)
Normalized poverty gap	0.5 (0.11)	0.7 (0.13)
Normalized mean positive poverty gap	15.8 (1.47)	16.8 (1.26)
<b>Poverty line = 1,883.5</b>		
Poverty head count	34.2 (1.56)	39.2 (1.59)
Poverty gap	160.5 (11.56)	192.3 (12.47)
Normalized poverty gap	8.5 (0.61)	10.2 (0.66)
Normalized mean positive poverty gap	24.9 (0.88)	26.0 (0.87)

Source: Author.

## Interpreting the Results

The first section of example table F5 uses a poverty line of D941,800 (Vietnamese dong) per year in 1998 prices. This corresponds to US\$1.08 per person per day. When assessed on the basis of total household consumption, 3.3 percent of the population is estimated to be in poverty. If out-of-pocket (OOP) payments for health care are netted out of household consumption, this percentage rises to 4.2. So about 1 percent of the population is not counted as living in poverty but would be considered poor if spending on health care were discounted from household resources. This represents a substantial rise of 30 percent in the estimate of poverty. The estimated poverty gap also rises almost 30 percent, from D4.9 to D6.6. The poverty gap increases from 0.5 percent of the poverty line to 0.7 percent when health payments are netted out of household consumption, but the normalized mean positive poverty gap increases only slightly (from 15.8 to 16.8). This suggests that the rise in the poverty gap is due mainly to more households being brought into poverty and not to a deepening of the poverty of the already poor. Finally, the second section of our example table uses a higher poverty line of D1,883.5. As expected, this results in a higher poverty head count and larger poverty gap.

## Share of Household Budgets

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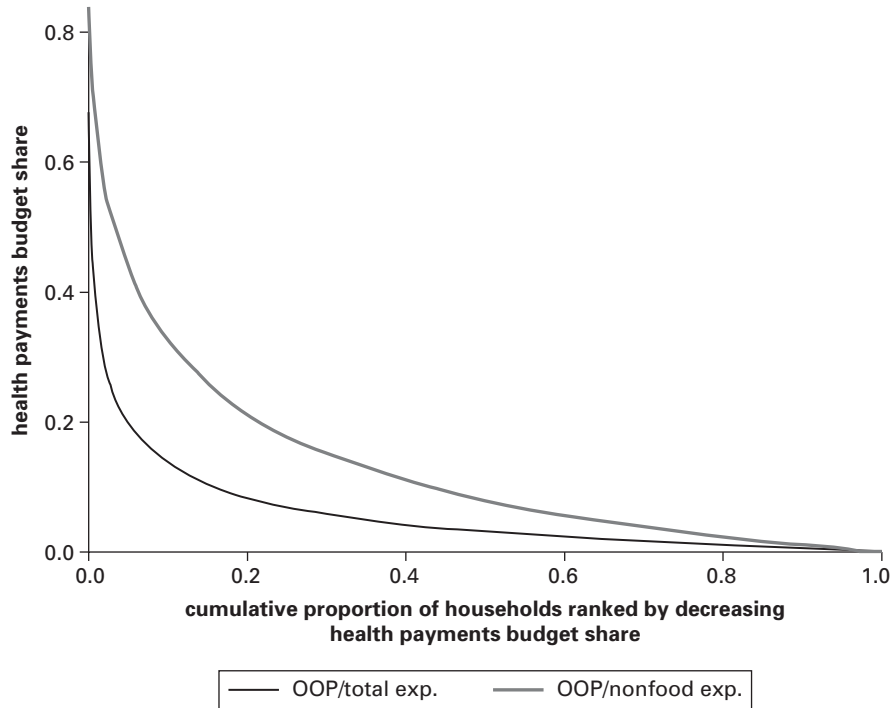
### Concepts

Graph GF1 puts the household payments budget share in relation to the cumulative fraction of households ranked by decreasing value of household prepayment budget share. Two curves are represented: one with the budget share computed as out-of-pocket health expenditure divided by total expenditure and another with the budget share expressed relative to household consumption net of food expenditure. This is a useful figure, as it shows how the catastrophic payment head count (the horizontal axis) depends on budget share threshold (the vertical axis). The flatter the curve, the more sensitive the head count is to choice of threshold.

## Interpreting the Results

In our example, the curve using total expenditure shows that a threshold of 5 percent leads to a catastrophic payment head count of 33.8 percent. When



**Graph GF1: Health Payment Shares**

Source: Author.

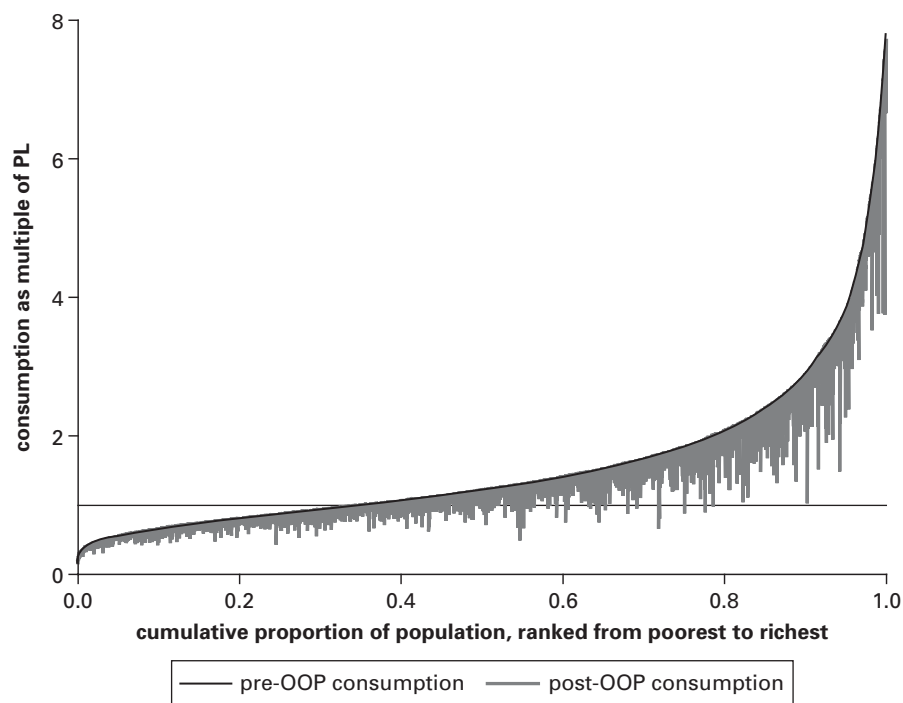
the threshold is raised to 10 percent, the proportion of households with catastrophic payments falls to 15.1 percent. If we further raise the threshold to 15 and 25 percent, the head count falls to 8.5 and 2.9 percent, respectively. These figures are displayed in table F1.

## Health Payments and Household Consumption

### Concepts

Graph GF2 is a stylized version of the Pen's parade representation of the income distribution. It charts household total consumption as a function of the cumulative proportion of households ranked in ascending order of total consumption. When health payments produce reranking in the income distribution, it is still possible to visualize the effect of health care

**Graph GF2: Effect of Health Payments on Pen's Parade of the Household Consumption**



Source: Author.

payments on the parade using what is referred to as a “paint drip” chart (Wagstaff and van Doorslaer 2003). The graph shows the Pen’s parade for household consumption gross of health payments. For each household, the vertical bar, or “paint drip” shows the extent to which health payments reduce consumption. If a bar crosses the poverty line, then a household is not poor on the basis of gross consumption, but is poor on the basis of net consumption. In other words, the household gets impoverished by health payments.<sup>1</sup>

### Interpreting the Results

Our example graph GF2 shows that health payments are largest at higher values of total consumption, but it is the households in the middle and lower half of the distribution that are brought below the poverty line by health payments.

## Progressivity and Redistributive Effect

### Concepts

Table P1 shows household health financing and total consumption by quintile, with households ranked in ascending order of gross consumption. For each quintile, the first column displays the average household total expenditure including health care payments, whereas the last column displays expenditure net of these. The other columns show the same information for each source of health finance along with total health financing. All financing and consumption variables are expressed in terms of values per equivalent adult in order to take household size and economies of scale into account. The last line provides information for the whole population. Finally, a standard error is displayed in parentheses below each estimate. When NHA weights are applied, table P1 presents only the part of each financing that contributes to the health system.

### Interpreting the Results

All example tables relating to progressivity and redistributive effect of health finance use the Egyptian data described in chapter 10. The first column in our example table P1 shows that the poorest quintile consumes,

**Table P1: Average Per Capita Health Finance**

	<i>Per capita consumption gross</i>	<i>Direct tax</i>	<i>Indirect tax</i>	<i>Cigarette tax</i>	<i>Social insurance contr.</i>	<i>Private insurance premiums</i>	<i>Out-of- pocket payments</i>	<i>Total payments</i>	<i>Per capita consumption net of payments</i>
<b>Quintiles of per capita consumption, gross</b>									
Lowest quintile	2,725.3 (39.13)	3.1 (1.17)	38.9 (2.30)	9.0 (0.64)	15.2 (1.43)	9.9 (2.53)	102.3 (13.38)	178.4 (15.27)	2,546.9 (39.60)
2	4,304.3 (17.52)	8.3 (2.37)	70.0 (2.84)	10.6 (0.79)	23.9 (1.72)	16.1 (3.47)	149.2 (13.41)	278.0 (14.41)	4,026.2 (21.41)
3	5,641.0 (20.42)	11.0 (2.21)	103.4 (3.83)	12.8 (1.00)	36.8 (3.56)	25.4 (3.97)	215.4 (20.50)	404.7 (22.50)	5,236.3 (27.98)
4	7,567.2 (41.63)	24.1 (5.66)	150.5 (5.41)	14.2 (1.00)	43.5 (2.81)	49.0 (11.38)	302.0 (36.43)	583.3 (39.79)	6,983.9 (49.89)
Highest quintile	14,516.9 (419.74)	83.8 (17.90)	423.0 (40.18)	36.7 (11.93)	66.0 (5.38)	54.4 (9.29)	669.2 (130.12)	1,333.0 (135.25)	13,183.9 (381.14)
<b>Total</b>	6,952.3 (196.95)	26.1 (4.45)	157.2 (10.83)	16.7 (2.45)	37.1 (2.06)	31.0 (4.12)	287.7 (31.34)	555.6 (36.78)	6,396.7 (174.69)

Source: Author.

on average, LE 2,725.3 and the richest consumes LE 14,516.9. When the population is taken as a whole (last line of the table), equivalent gross consumption amounts to LE 6,952.3. Direct taxes appear to be borne mostly by the richest, as the first three quintiles contribute only LE 3.1, LE 8.3, and LE 11.0, on average, whereas the last two contribute LE 24.1 and LE 83.8, respectively. The average financing increases with quintile for all other sources of financing, but differences are, in general, less marked than for direct taxes. In the case of cigarette taxes, the richest quintile (LE 36.7) contributes only four times as much as the poorest one (LE 9.0). The optional NHA weights were applied in this example. The table thus displays the entire sources of financing, irrespective of their final contribution to the health system.

## Progressivity of Health Financing

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### Concepts

Tables P2 and P3 allow us to analyze the progressivity of health financing. The first part of table P2 gives the average consumption and financing share, by quintile, with households ranked in ascending order of gross consumption. Information related to consumption gives an idea about income inequality: the greater the share of the richest quintiles, the greater is the inequality. The sources of financing show which part of the income distribution bears the financing: the greater the share of the richest, the more concentrated is the financing among the rich or, put differently, the more pro-rich the financing. Table P3 is similar to table P2, with the only exception being that it expresses health financing as a share of total gross consumption. This additional table thus shows the size of each source of financing in terms of its budget share.

The second part of both tables provides measures of financing concentration and progressivity. The first line gives the prefinancing and postfinancing income inequality as measured by the Gini index. The second line shows the financing concentration index, which indicates how financing is related to income. A positive value indicates that the rich bear a greater share of the financing than the poor (that is, pro-poor financing), whereas a negative value indicates the opposite. A concentration

**Table P2: Shares of Total Financing**

	<i>Per capita consumption gross</i>	<i>Direct tax</i>	<i>Indirect tax</i>	<i>Cigarette tax</i>	<i>Social insurance contr.</i>	<i>Private insurance premiums</i>	<i>Out-of- pocket payments</i>	<i>Total payments</i>	<i>Per capita consumption net of payments</i>
<b>Quintiles of per capita consumption, gross</b>									
Lowest quintile	7.8 (0.73)	2.4 (0.93)	4.9 (0.72)	10.8 (2.12)	8.2 (1.24)	6.4 (1.75)	7.1 (1.33)	6.4 (0.94)	8.0 (0.73)
2	12.4 (0.80)	6.3 (1.80)	8.9 (0.81)	12.7 (2.23)	12.9 (1.29)	10.4 (2.22)	10.4 (1.40)	10.0 (0.95)	12.6 (0.81)
3	16.2 (0.96)	8.4 (1.87)	13.2 (1.31)	15.3 (2.65)	19.9 (1.95)	16.4 (2.61)	15.0 (2.14)	14.6 (1.45)	16.4 (0.94)
4	21.8 (0.97)	18.5 (3.44)	19.1 (1.24)	17.1 (2.41)	23.5 (1.50)	31.7 (4.79)	21.0 (2.87)	21.0 (1.77)	21.8 (0.96)
Highest quintile	41.8 (2.19)	64.4 (4.72)	53.9 (3.18)	44.0 (8.35)	35.6 (2.99)	35.1 (4.51)	46.6 (5.71)	48.0 (3.66)	41.2 (2.14)
Total	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)	100.0 (0.00)
Gini coefficient	0.3343 (0.0127)								0.3321 (0.0124)
Concentration Index		0.5843 (0.0438)	0.4778 (0.0271)	0.3282 (0.0970)	0.2811 (0.0209)	0.3332 (0.0448)	0.3987 (0.0550)	0.4161 (0.0313)	
Kakwani index		0.2500 (0.0424)	0.1434 (0.0192)	-0.0061 (0.0972)	-0.0532 (0.0183)	-0.0011 (0.0445)	0.0643 (0.0515)	0.0818 (0.0259)	

Source: Author.

**Table P3: Financing Budget Shares**

	<i>Per capita consumption gross</i>	<i>Direct tax</i>	<i>Indirect tax</i>	<i>Cigarette tax</i>	<i>Social insurance contr.</i>	<i>Private insurance premiums</i>	<i>Out-of- pocket payments</i>	<i>Total payments</i>	<i>Per capita consumption net of payments</i>
<b>Quintiles of per capita consumption, gross</b>									
Lowest quintile	100.0 (0.00)	0.1 (0.04)	1.4 (0.08)	0.3 (0.02)	0.6 (0.05)	0.4 (0.09)	3.8 (0.49)	6.5 (0.54)	93.5 (0.54)
2	100.0 (0.00)	0.2 (0.05)	1.6 (0.06)	0.2 (0.02)	0.6 (0.04)	0.4 (0.08)	3.5 (0.31)	6.5 (0.33)	93.5 (0.33)
3	100.0 (0.00)	0.2 (0.04)	1.8 (0.07)	0.2 (0.02)	0.7 (0.06)	0.5 (0.07)	3.8 (0.36)	7.2 (0.40)	92.8 (0.40)
4	100.0 (0.00)	0.3 (0.07)	2.0 (0.07)	0.2 (0.01)	0.6 (0.04)	0.6 (0.15)	4.0 (0.48)	7.7 (0.51)	92.3 (0.51)
Highest quintile	100.0 (0.00)	0.6 (0.13)	2.9 (0.22)	0.3 (0.08)	0.5 (0.03)	0.4 (0.07)	4.6 (0.88)	9.2 (0.85)	90.8 (0.85)
Total	100.0 (0.00)	0.4 (0.06)	2.3 (0.12)	0.2 (0.03)	0.5 (0.03)	0.4 (0.06)	4.1 (0.42)	8.0 (0.41)	92.0 (0.41)
Gini coefficient	0.3343 (0.0127)								0.3321 (0.0124)
Concentration Index		0.5843 (0.0438)	0.4778 (0.0271)	0.3282 (0.0970)	0.2811 (0.0209)	0.3332 (0.0448)	0.3987 (0.0550)	0.4161 (0.0313)	
Kakwani index		0.2500 (0.0424)	0.1434 (0.0192)	-0.0061 (0.0972)	-0.0532 (0.0183)	-0.0011 (0.0445)	0.0643 (0.0515)	0.0818 (0.0259)	

Source: Author.

index not significantly different from 0 reflects no relationship between income and financing.

The Kakwani index is the key information in tables P2 and P3. This index measures financing progressivity as the difference between the concentration index and the gross consumption Gini index. A positive value reveals that financing is more concentrated among the rich than income, which indicates progressivity. A simpler way to think about progressivity is that the financing budget share (that is, financing divided by income) increases with income.

### Interpreting the Results

The first part of our example table P2 shows that the poorest quintile consumes, on average, 7.8 percent of total consumption, whereas this amounts to 41.8 percent for the richest. Direct taxes appear to be borne mostly by the richest, as the first three quintiles contribute only 2.4, 6.3, and 8.4 percent, on average, whereas the last two contribute 18.5 and 64.4 percent, respectively. The financing share increases by quintile for all other sources of financing, but differences are, in general, less marked than for direct taxes. In the case of cigarette taxes, the richest quintile (44.0 percent) contributes only four times as much as the poorest one (10.8 percent). Table P3 shows that the largest sources of financing are out-of-pocket expenditure and indirect taxes, which, respectively, represent about 4 and 2 percent of gross consumption.

All concentration indexes are positive, indicating that the better off contribute absolutely more to the financing of health care than do the poor. The concentration index is largest for direct taxes (0.5843) and smallest for social insurance contributions (0.2811), suggesting that direct taxes are the most progressive and social insurance contributions are the least so.

The Kakwani indexes for both direct (0.2500) and indirect (0.1434) taxes are clearly positive, indicating progressivity. This is also the case, but a bit less marked, for out-of-pocket payments (0.0643). The Kakwani index is very close to 0 for cigarette taxes and private insurance and is moderately negative for social insurance contributions ( $-0.0532$ ), indicating regressivity. The magnitude of the latter index is reduced by the near proportionality in the bottom half of the income distribution. This is difficult to see here, which is why graphs (such as graph GP2, for instance) are also necessary when assessing progressivity of financing.

## Decomposition of Redistributive Effect of Health Financing

### Concepts

Table P4 provides a decomposition of the redistributive effect of health financing. As in table P2, the first part gives the average consumption and financing share by quintile, with households ranked in ascending order of gross consumption.

The second part of the table starts by presenting the average financing budget share ( $g$ ), that is, the average ratio of household financing to gross consumption, providing us with a measure of financing size. The second line gives the Kakwani index ( $K_e$ ) of a counterfactual financing system in which horizontal inequity has been neutralized by averaging financing over gross income classes.  $K_e$  represents the progressivity that would be observed if financing were not causing any differential treatment of equals.

The next four lines provide the decomposition of the redistributive effect of Aronson, Johnson, and Lambert (1994). The vertical effect,  $V$ , represents the change in income inequality that would be caused by financing in the

**Table P4: Decomposition of Redistributive Impact of Health Care Financing System**

	<i>Per capita consumption gross</i>	<i>Direct tax</i>	<i>Indirect tax</i>	<i>Cigarette tax</i>	<i>Social insurance contr.</i>	<i>Private insurance premiums</i>	<i>Out-of- pocket payments</i>	<i>Total payments</i>
<b>Quintiles of per capita gross consumption</b>								
Lowest quintile	7.8	2.4	4.9	10.8	8.2	6.4	7.1	6.4
2	12.4	6.3	8.9	12.7	12.9	10.4	10.4	10.0
3	16.2	8.4	13.2	15.3	19.9	16.4	15.0	14.6
4	21.8	18.5	19.1	17.1	23.5	31.7	21.0	21.0
Highest quintile	41.8	64.4	53.9	44.0	35.6	35.1	46.6	48.0
Total 100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	
Payments as fraction of Income ( $g$ )	1.0000	0.0037	0.0226	0.0024	0.0053	0.0045	0.0414	0.0799
Kakwani index, assuming horizontal equity ( $K_e$ )		0.2497	0.1440	-0.0033	-0.0536	-0.0017	0.0600	0.0795
Vertical effect ( $V$ )		9.40E-04	3.33E-03	-8.00E-06	-2.87E-04	-7.40E-06	2.59E-03	6.91E-03
Horizontal inequality ( $H$ )		5.35E-05	6.79E-05	1.14E-05	2.37E-05	1.05E-04	1.03E-03	1.39E-03
Reranking ( $R$ )		7.57E-05	6.67E-06	6.83E-08	5.74E-06	4.21E-05	2.48E-03	3.33E-03
Total redistributive effect ( $RE = V - H - R$ )		8.10E-04	3.26E-03	-1.94E-05	-3.17E-04	-1.55E-04	-9.18E-04	2.18E-03
$V / RE$		1.1594	1.0229	0.4115	0.9071	0.0478		3.1638
$H / RE$		0.0660	0.0208	-0.5849	-0.0748	-0.6797		0.6365
$R / RE$		0.0934	0.0020	-0.0035	-0.0181	-0.2725		1.5273

Source: Author.

absence of differential treatment of equals. A positive effect indicates a reduction in inequality, whereas a negative value reflects an increase in inequality.  $H$  is a measure of horizontal inequity—that is, the increase in income inequality due to unequal treatment of households with the same prefinancing income.  $R$  represents the increase in income inequality due to reranking—that is, the change in the rank order of households in the income distribution that is caused by financing. The next line of the table displays the total redistributive effect ( $RE$ ), which measures the overall change in income inequality resulting from financing. The total redistributive effect equals the vertical effect minus horizontal inequality and reranking. Finally, since the decomposition effects are usually small, it is often easier to interpret their values relative to the total redistributive effect. This is displayed in the last three lines of the table. However, note that when  $V$  and  $RE$  have opposite signs, this ratio is misleading, and ADePT does not produce it.

### Interpreting the Results

The first part of our example table P4 shows that the poorest quintile consumes, on average, 7.8 percent of total consumption, whereas the richest quintile consumes 41.8 percent. Direct taxes appear to be borne mostly by the richest: the first three quintiles contribute only 2.4, 6.3, and 8.4 percent, on average, whereas the last two contribute 18.5 and 64.4 percent, respectively. The financing share increases as the quintile rises for all other sources of financing, but differences are less marked than for direct taxes. In the case of cigarette taxes, the richest quintile (44.0 percent) contributes only four times as much as the poorest one (10.8).

The second part of the table shows that out-of-pocket health expenditure is the greatest source of financing, as it represents 4.14 percent of the household budget, on average. With 2.26 percent, indirect taxes are the second largest source of financing, followed by social insurance contributions, which only amount to 0.53 percent of household gross income. In the absence of horizontal inequity, indirect taxes would have a Kakwani index of 0.1440, which indicates progressivity. Out-of-pocket payments would also be progressive, but less so (0.0600), whereas social insurance contributions would be regressive ( $-0.0536$ ).

The total redistributive effect of indirect taxes shows a decrease in income inequality ( $3.26E-03$ ). This is also the case for direct taxes ( $8.10E-04$ ),



whereas out-of-pocket health expenditure ( $-9.18\text{E-}04$ ) and social insurance contributions ( $-3.17\text{E-}04$ ) have the opposite effect.

When decomposing the total redistributive effect, the decrease in income inequality due to indirect taxes is mostly a vertical effect, as the ratio  $V / RE$  is close to 1 (1.0229). Inequality is thus reduced because the rich pay more indirect taxes relative to their income. The ratio  $V / RE$  for direct taxes equals 1.1594, which means that the positive redistributive effect of direct taxes would be 16 percent greater in the absence of horizontal inequity (that is,  $H + R$ ). The negative redistributive effect (in other words, the increase in income inequality) caused by social health insurance, at 90.7 percent, is due to a negative vertical effect ( $V / RE = 0.9071$ ) and, at 9.3 percent, is due to horizontal inequity. Note that  $V / RE$  is much farther from 100 percent in the case of cigarette taxes and (even more so) private insurance premiums, indicating that for these sources there is considerable variation in the amount paid at a given level of income. Finally, since  $RE$  and  $V$  have opposite signs for out-of-pocket health expenditure, it is not possible to interpret the relative measures of the decomposition. The analysis of the corresponding absolute values shows that this financing has a strong positive vertical effect. This means that the rich contribute proportionally more than the poor, which is very likely due to a greater use of health care. Finally, the very strong horizontal inequity observed is likely to come from the health heterogeneity in the population.

## Concentration Curves

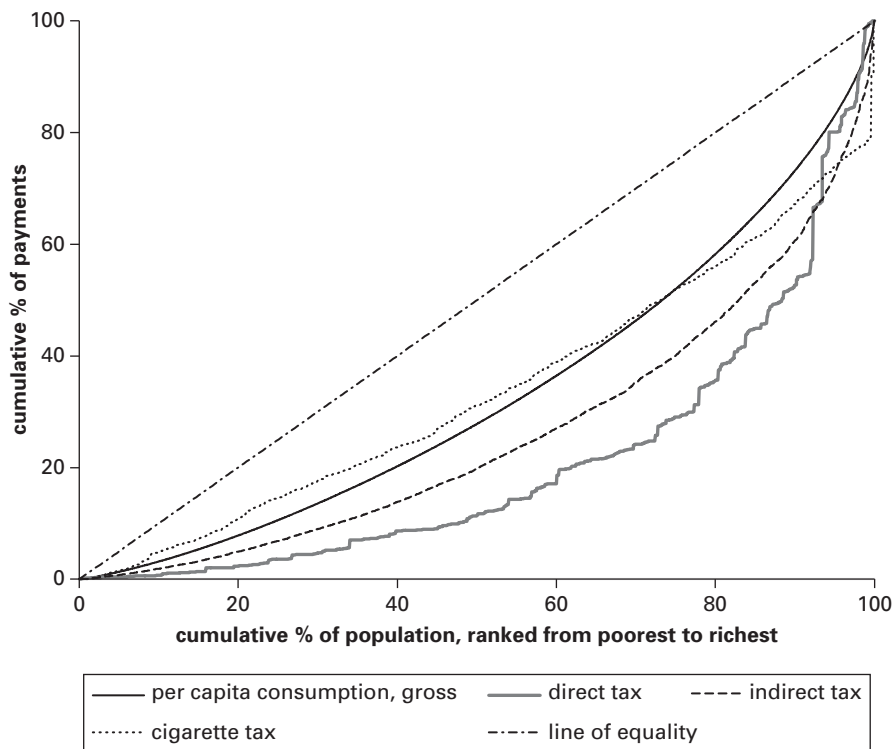
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### Concepts

Graphs GP1 and GP2 present the Lorenz curve for household total expenditure gross of health payments along with the concentration curve for each source of household health financing. The difference between these two graphs is that GP1 shows household taxes, whereas GP2 displays social insurance contributions, private insurance premiums, and out-of-pocket payments.

The Lorenz curve shows the cumulative share of consumption according to the cumulative share of population ranked in ascending order of consumption. For instance, only 20 percent of total consumption might come from the poorest 30 percent of the population. This curve provides us with a visual representation of household inequality: the farther the curve is from the  $45^\circ$  line, the greater is the inequality.

**Graph GP1: Concentration Curves for Health Payments, Taxes**

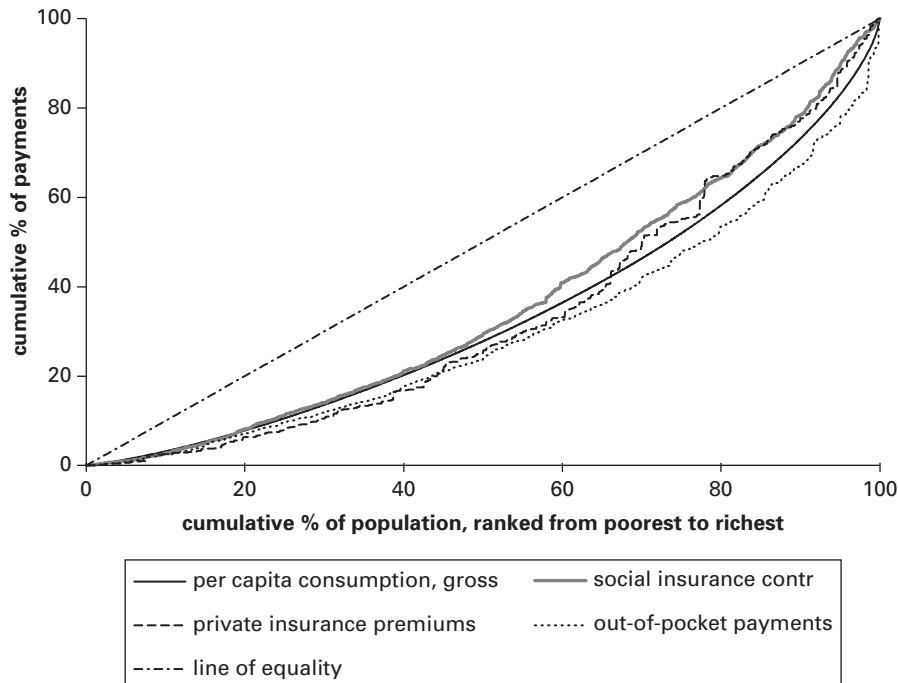


Source: Author.

The concentration curves represent the cumulative share of health payments according to the cumulative share of population, again ranked in ascending order of consumption. For instance, the poorest 30 percent might contribute only 10 percent to total taxes. These curves show how health financing varies according to consumption: the farther a curve is from the 45° line, the more the corresponding source of financing is borne by the richest households. For some sources of financing, the concentration curve might lie above the 45° line. In such cases, payments are more concentrated among the poorest households.

Furthermore, these graphs offer a powerful means of representing the effect of health financing on the distribution of household living standards. Indeed, whenever a concentration curve lies outside the Lorenz curve, this indicates progressivity. However, a formal test of statistical dominance is required to conclude this definitively (see O'Donnell and others 2008, ch. 7).

**Graph GP2: Concentration Curves for Health Payments, Insurance, Out of Pocket**



Source: Author.

Finally, it should be borne in mind that this kind of analysis does not consider utilization of health care. Progressivity should thus not be interpreted as the rich paying more for the same amount of health care, as this is most often not the case and not accounted for by the measures presented here.

### Interpreting the Results

In our example graph GP1, the concentration curves for direct and indirect taxes appear to lie outside the Lorenz curve, suggesting that these are progressive sources of finance. The curve for the earmarked cigarette tax appears to lie inside the Lorenz curve at lower levels of consumption but outside it at higher levels of consumption. This suggests regressivity in the first part of the consumption distribution and then progressivity for the richest households. However, the gap between the concentration and Lorenz curves is never wide.

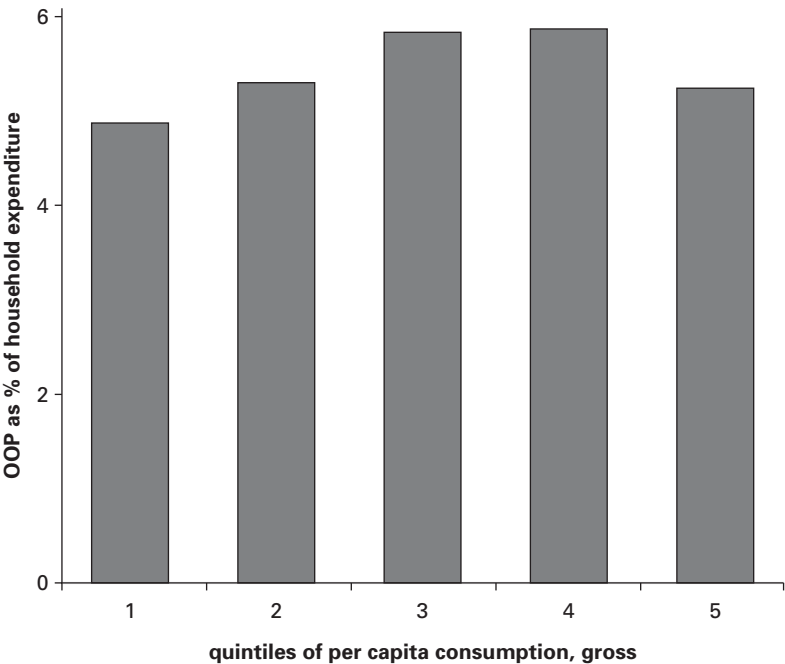
Our example graph GP2 shows that the concentration curve for out-of-pocket payments lies outside the Lorenz curve, suggesting progressivity. Although the concentration curve for private insurance premiums lies below the Lorenz curve at lower consumption, the opposite is true at higher consumption. The concentration curve for social insurance contributions lies almost exactly on top of the Lorenz curve (indicating proportionality) up to the middle of the consumption distribution, but lies inside the Lorenz curve for the top half of the distribution. Social insurance premiums thus seem regressive, but only at the top of the distribution.

## Distribution of Health Payments

### Concepts

Graph GP3 shows the average budget share of out-of-pocket health payments (that is, health payments divided by total expenditure) by quintile of

**Graph GP3: Health Payment Shares by Quintiles**



Source: Author.

gross per capita consumption. This graph is a direct representation of the progressivity of health payments. These are progressive if their share of household consumption increases with consumption and are regressive in the opposite case. Finally, if their budget share does not vary with consumption, health payments are proportional to income.

### Interpreting the Results

Our example shows that out-of-pocket payments are progressive over the first three quintiles, then stabilize, and finally become regressive for the richest quintile.

### Note

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1. This interpretation is discussed in technical note 18 in chapter 13.

### References

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- Aronson, J. R., P. Johnson, and P. J. Lambert. 1994. "Redistributive Effect and Unequal Tax Treatment." *Economic Journal* 104 (423): 262–70.
- O'Donnell, O., E. van Doorslaer, A. Wagstaff, and M. Lindelow. 2008. *Analyzing Health Equity Using Household Survey Data: A Guide to Techniques and Their Implementation*. Washington, DC: World Bank.
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# Technical Notes

These technical notes are intended as a brief guide for users of ADePT Health Financing. They are drawn largely (and often with minimal changes) from O'Donnell and others (2008), which provides further information.

## Financial Protection

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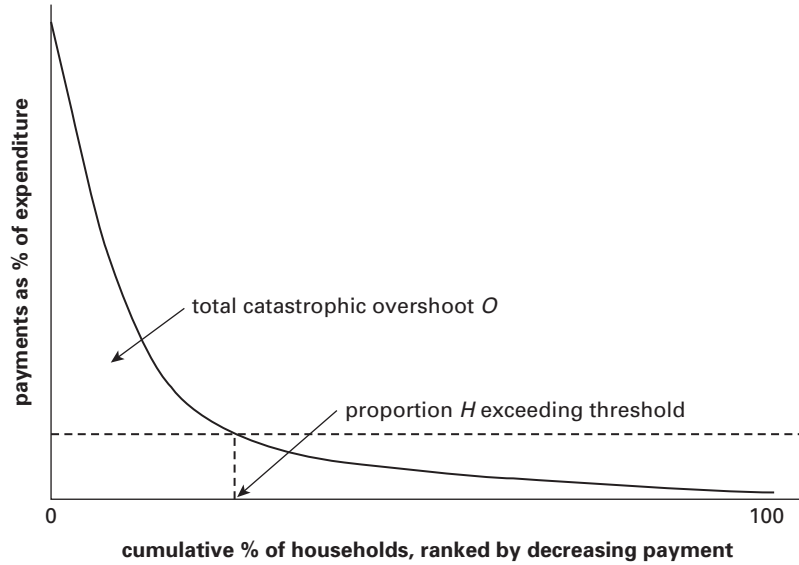
### Note 12: Measuring Incidence and Intensity of Catastrophic Payments

Measures of the incidence and intensity of catastrophic payments can be defined analogously to those for poverty. The incidence of catastrophic payments can be estimated from the fraction of a sample with health care costs as a share of total (or nonfood) expenditure exceeding the chosen threshold. The horizontal axis in figure 13.1 shows the cumulative fraction of households ordered by the ratio  $T/x$  from largest to smallest.<sup>1</sup> The graph shows the fraction ( $H$ ) of households with health care budget shares that exceed threshold  $z$ . This is the catastrophic payment head count. Define an indicator,  $E$ , which equals 1 if  $T_i/x_i > z$  and 0 otherwise. Then an estimate of the head count is given by

$$H = \frac{1}{N} \sum_{i=1}^N E_i, \quad (13.1)$$

where  $N$  is the sample size.

**Figure 13.1: Health Payments Budget Share and Cumulative Percentage of Households Ranked by Decreasing Budget Share**



Source: O'Donnell and others 2008.

This measure does not reflect the amount by which households exceed the threshold. Another measure, the catastrophic payment overshoot, captures the average degree by which payments (as a proportion of total expenditure) exceed threshold  $z$ . Define the household overshoot as  $O_i = E_i[(T_i / x_i) - z]$ . Then the overshoot is simply the average:

$$O = \frac{1}{N} \sum_{i=1}^N O_i. \quad (13.2)$$

In figure 13.1,  $O$  is indicated by the area under the payment share curve but above the threshold level. It is clear that although  $H$  captures only the occurrence of a catastrophe,  $O$  captures the intensity of the occurrence as well. They are related through the mean positive overshoot, which is defined as follows:

$$MPO = \frac{O}{H}. \quad (13.3)$$

Because this implies that  $O = H \times MPO$ , the catastrophic overshoot equals the fraction with catastrophic payments times the mean positive



overshoot—the incidence times the intensity. Obviously, all of these can also be defined with  $x - f(x)$  as the denominator.

### Note 13: Distribution-Sensitive Measures of Catastrophic Payments

All the measures introduced in technical note 12 are insensitive to the distribution of catastrophic payments. In the head count, all households exceeding the threshold are counted equally. The overshoot counts equally all dollars spent on health care in excess of the threshold, irrespective of whether they are made by the poor or by the rich. If there is diminishing marginal utility of income, the opportunity cost of health spending by the poor will be greater than that by the rich. If one wishes to place a social welfare interpretation on measures of catastrophic payments, then it might be argued that they should be weighted to reflect this differential opportunity cost.

The distribution of catastrophic payments in relation to income could be measured by concentration indexes for  $E_i$  and  $O_i$ . Label these indexes  $C_E$  and  $C_O$ . A positive value of  $C_E$  indicates a greater tendency for the better off to exceed the payment threshold; a negative value indicates that the worse off are more likely to exceed the threshold. Similarly, a positive value of  $C_O$  indicates that the overshoot tends to be greater among the better off. One way of adjusting the head count and overshoot measures of catastrophic payments to take into account the distribution of payments is to multiply each measure by the complement of the respective concentration index (Wagstaff and van Doorslaer 2003). That is, the following weighted head count and overshoot measures are computed:

$$H^W = H \cdot (1 - C_E) \quad (13.4)$$

and

$$O^W = O \cdot (1 - C_O). \quad (13.5)$$

The measures imply value judgments about how catastrophic payments incurred by the poor are weighted relative to those incurred by the better off. The imposition of value judgments is unavoidable in producing any distribution-sensitive measure. In fact, it could be argued that a distribution-insensitive measure itself imposes a value judgment—catastrophic payments are weighed equally irrespective of who incurs them. The particular weighting scheme imposed by equation 13.4 is that the household with the lowest

income receives a weight of 2, and the weight declines linearly with rank in the income distributions so that the richest household receives a weight of 0. So if the poorest household incurs catastrophic payments, it is counted twice in the construction of  $H^W$ , whereas if the richest household incurs catastrophic payments, it is not counted at all. A similar interpretation holds for equation 13.5. Obviously, different weighting schemes could be proposed to construct alternatives to these rank-dependent weighted head count and overshoot indexes.

If those who exceed the catastrophic payments threshold tend to be poorer, the concentration index ( $C_E$ ) will be negative, and this will make  $H^W$  greater than  $H$ . From a social welfare perspective and given the distributional judgments imposed, the catastrophic payment problem is worse than it appears simply by looking at the fraction of the population exceeding the threshold because it overlooks the fact that it tends to be the poor who exceed the threshold. However, if it is the better-off individuals who tend to exceed the threshold,  $C_E$  will be positive, and  $H$  will overstate the problem of the catastrophic payments as measured by  $H^W$ . A similar interpretation holds for comparisons between  $O$  and  $O^W$ .

#### **Note 14: Threshold Choice**

The value of threshold  $z$  represents the point at which the absorption of household resources by spending on health care is considered to impose a severe disruption to living standards. That is obviously a matter of judgment. Researchers should not impose their own judgment but rather should present results for a range of values of  $z$  and let readers choose where to give more weight. The value of  $z$  will depend on whether the denominator is total expenditure or nondiscretionary expenditure. Spending 10 percent of total expenditure on health care might be considered catastrophic, but 10 percent of nondiscretionary expenditure probably would not. In the literature, when total expenditure is used as the denominator, the most common threshold that has been used is 10 percent (Pradhan and Prescott 2002; Ranson 2002; Wagstaff and van Doorslaer 2003), with the rationale being that this represents an approximate threshold at which the household is forced to sacrifice other basic needs, sell productive assets, incur debt, or become impoverished (Russell 2004). Researchers from the World Health Organization have used 40 percent (Xu and others 2003) when “capacity to pay” (roughly, nonfood expenditure) is used as the denominator.

### **Note 15: Limitations of the Catastrophic Payment Approach**

The idea underlying the catastrophic payments approach is that spending a large fraction of the household budget on health care must be at the expense of the consumption of other goods and services. This opportunity cost may be incurred in the short term if health care is financed by cutting back on current consumption or in the long term if it is financed through savings, the sale of assets, or credit. With cross-sectional data, it is impossible to distinguish between the two.

Besides this, there are other limitations of the approach. First, it identifies only the households that incur catastrophic medical expenditures and ignores those that cannot meet these expenses and so forgo treatment. Through the subsequent deterioration of health, such households probably suffer a greater welfare loss than those incurring catastrophic payments. Recognizing this, Pradhan and Prescott (2002) estimate exposure to, rather than incurrence of, catastrophic payments.

Second, in addition to medical spending, illness shocks have catastrophic economic consequences through lost earnings. Gertler and Gruber (2002) find that in Indonesia earnings losses are more important than medical spending in disrupting household living standards following a health shock.

Third, the approach depends on the measure of household resources, which can be household income or consumption measured by household expenditure. Of these, only income is not directly responsive to medical spending. That may be considered an advantage. However, the health payments-to-income ratio is not responsive to the means of financing health care, and that may be considered a disadvantage. Consider two households with the same income and health payments. Say, one household has savings and finances health care from savings, whereas the other has no savings and must cut back on current consumption to pay for health care. This difference is not reflected in the ratio of health payments to income, which is the same for both households. But the ratio of health payments to total household expenditure will be larger for the household without savings. Assuming that the opportunity cost of current consumption is greater, the “catastrophic impact” is greater for the household without savings, and, to an extent, this will be reflected if expenditure, but not income, is used as the denominator in the definition of catastrophic payments.

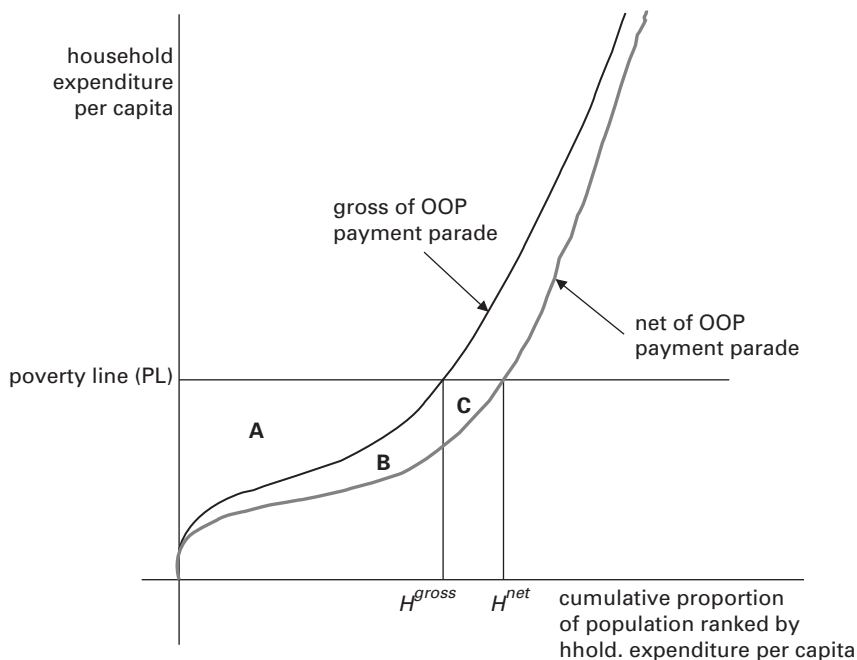
Notwithstanding these limitations, medical spending in excess of a substantial fraction of the household budget is informative of at least part of the

catastrophic economic consequences of illness, without fully identifying the welfare loss from lack of financing protection against health shocks.

### Note 16: Health Payments–Adjusted Poverty Measures

Let  $T$  be per capita household out-of-pocket spending on health care, and let  $x$  be the per capita living standards proxy that is used in the standard assessment of poverty—household expenditure, consumption, or income. For convenience, we refer to the living standards variable as household expenditure. Figure 13.2 provides a simple framework for examining the impact of out-of-pocket payments on the two basic measures of poverty—the head count and the poverty gap. The figure is a variant on Jan Pen’s “parade of dwarfs and a few giants” (see, for example, Cowell 1995). The two parades plot household expenditure gross and net of out-of-pocket payments on the y axis against the cumulative proportion of individuals ranked by expenditure on the x axis. For this stylized version of the graph, we assume that households

**Figure 13.2: Pen’s Parade for Household Expenditure Gross and Net of Out-of-Pocket Health Payments**



Source: O'Donnell and others 2008.  
Note: OOP = out of pocket.

keep the same rank in the distribution of gross and net out-of-pocket expenditure. In reality, reranking will occur, as illustrated by ADePT graph F2. The point on the x axis at which a curve crosses the poverty line ( $PL$ ) gives the fraction of people living in poverty. This is the poverty head count ratio ( $H$ ). This measure does not capture the “depth” of poverty—that is, the amount by which poor households fall short of reaching the poverty line. A measure that does take the depth of poverty into account is the poverty gap ( $G$ ), defined as the area below the poverty line but above the parade.

Using household expenditure gross of out-of-pocket payments for health care, the poverty head count is  $H^{gross}$  and the poverty gap is equal to the area  $A$ . If out-of-pocket payments are subtracted from household expenditure before poverty is assessed, then the head count and gap must both rise—to  $H^{net}$  and  $A + B + C$ , respectively. So  $H^{net} - H^{gross}$  is the fraction of individuals who are not counted as poor even though their household resources net of spending on health care are below the poverty line. The respective underestimate of the poverty gap is  $B + C$ . The poverty gap increases both because those already counted as poor appear even poorer once health payments are netted out of household resources (area  $B$ ) and because some who were not counted as poor on the basis of gross expenditures are assessed as poor after out-of-pocket payments (area  $C$ ) are taken into account.

Let  $x_i$  be the per capita total expenditure of household  $i$ . An estimate of the gross of health payments poverty head count ratio is

$$H^{gross} = \frac{\sum_{i=1}^N s_i p_i^{gross}}{\sum_{i=1}^N s_i}, \quad (13.6)$$

where  $p_i^{gross} = 1$  if  $x_i < PL$  and is 0 otherwise,  $s_i$  is the size of the household, and  $N$  is the number of households in the sample. Defining the gross of health payments individual-level poverty gap by  $g_i^{gross} = p_i^{gross} (PL - x_i)$ , the mean of this gap in currency units is

$$G^{gross} = \frac{\sum_{i=1}^N s_i g_i^{gross}}{\sum_{i=1}^N s_i}. \quad (13.7)$$

The net of health payments head count is given by replacing  $p_i^{gross}$  with  $p_i^{net} = 1$  if  $(x_i - T_i) < PL$  (and 0 otherwise) in equation 13.6. The net of health payments poverty gap is given by replacing  $g_i^{gross}$  in equation 13.7 with  $g_i^{net} = p_i^{net} [PL - (x_i - T_i)]$ .

When making comparisons across countries with different poverty lines and currency units, it is convenient to normalize the poverty gap on the poverty line as follows:

$$NG^{gross} = \frac{G^{gross}}{PL}. \quad (13.8)$$

The net of payments normalized gap is defined analogously. The intensity of poverty alone is measured by the mean positive poverty gap,

$$MPG^{gross} = \frac{G^{gross}}{H^{gross}}. \quad (13.9)$$

In other words, the poverty gap ( $G$ ) is equal to the fraction of the population who are poor ( $H$ ) multiplied by the average deficit of the poor from the poverty line ( $MPG$ ). The mean positive poverty gap can also be normalized on the poverty line.

### Note 17: Adjusting the Poverty Line

It might be argued that if poverty is to be assessed on the basis of household expenditure net of out-of-pocket payments for health care, then the poverty line should also be adjusted downward. This would be correct if the poverty line allowed for resources required to cover health care needs. Poverty lines that indicate resources required to cover only subsistence food needs clearly do not. Higher poverty lines may make some indirect allowance for expected health care needs, but they can never fully reflect these needs, which are inherently highly variable, both across individuals and across time. A common procedure for constructing a poverty line involves calculating expenditure required to meet subsistence nutrition requirements and the addition of an allowance for nonfood needs (Deaton 1997). More directly, the mean total expenditure of households just satisfying their nutritional requirements may be used as the poverty line. Implicitly, this takes into account the expected spending on health care of those in the region of food poverty. But there is tremendous variation across households in health status and therefore in health care needs, which will not be reflected in the poverty line. This may be less of a problem in high-income countries, in which explicit income transfers exist to cover the living costs of disability. But such transfers seldom exist in low-income countries. Further, the health care needs of a given household are

stochastic over time. A person falling seriously ill faces health care expenses well above the average. Meeting these expenses can easily force spending on other goods and services below the poverty threshold.

So there is no reason to adjust a subsistence food poverty line, but higher poverty lines may make some implicit allowance for expected health care needs; in this case, it would make sense to adjust the poverty line downward when assessing poverty on expenditure net of health payments. One option is to adjust the poverty line downward by the mean health spending of households with total expenditure in the region of the poverty line (Wagstaff and van Doorslaer 2003). If that practice is adopted, then obviously some households who spend less on health care than this average can be drawn out of poverty when it is assessed on expenditure net of health care payments. That practice is not advisable if comparisons are being made across countries or time and the standard poverty line has not been adjusted to reflect differences in mean health payments in the region with food poverty. For example, the World Bank poverty lines of \$1 or \$2 a day clearly do not reflect differences across countries in poor households' exposure to health payments. Subtracting country-specific means of health spending from these amounts would result in lower poverty lines, and so less poverty, in countries that protect low-income households the least from the cost of health care.

### **Note 18: On the Impoverishing Effect of Health Payments**

Under two conditions, the difference between poverty estimates derived from household resources gross and net of out-of-pocket payments for health care may be interpreted as a rough approximation of the impoverishing effect of such payments (Wagstaff and van Doorslaer 2003). These conditions are as follows:

- Out-of-pocket payments are completely nondiscretionary.
- Total household resources are fixed.

Under these conditions, the difference between the two estimates would correspond to poverty due to health payments. Neither of the two conditions holds perfectly, though. A household that chooses to spend excessively on health care is not pushed into poverty by out-of-pocket payments. In addition, a household may borrow, sell assets, or receive transfers

from friends or relatives to cover health care expenses. Household expenditure gross of out-of-pocket payments does not correspond to the consumption that would be realized in the absence of those payments. For these and other reasons, a simple comparison between poverty estimates that do and do not take into account out-of-pocket health payments cannot be interpreted as the change in poverty that would arise from some policy reform that eliminated those payments. Nonetheless, such a comparison is indicative of the extent of the impoverishing effect of health payments.

### Progressivity and Redistributive Effect

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#### Note 19: Measuring Progressivity

The most direct means of assessing progressivity of health payments is to examine their share of ability to pay as the latter varies. If we observe a tendency for this share to rise with total expenditure, this would indicate some degree of progressivity in financing. ADePT graph P3 can be used for such an analysis.

A less direct means of assessing progressivity, defined in relation to departure from proportionality, is to compare shares of health payments contributed by proportions of the population ranked by ability to pay with their share of ability to pay—that is, to compare the concentration curve for health payments,  $L_H(p)$ , with the Lorenz curve for ability to pay,  $L(p)$ . If payments toward health care always account for the same proportion of ability to pay, then the share of health payments contributed by any group must correspond to its share of ability to pay. The concentration curve lies on top of the Lorenz curve. Under a progressive system, the share of health payments contributed by the poor will be less than their share of ability to pay. The Lorenz curve dominates (lies above) the concentration curve. The opposite is true for a regressive system. ADePT Health Financing provides graphs P1 and P2 to analyze dominance. However, it is currently not possible to test formally for stochastic dominance using ADePT.<sup>2</sup>

Lorenz dominance analysis is the most general way of detecting departures from proportionality and identifying their location in the distribution of ability to pay. But it does not provide a measure of the magnitude of progressivity, which may be useful when making comparisons across time or countries. Summary indexes of progressivity meet this deficiency but require



the imposition of value judgments about the weight given to departures from proportionality at different points in the distribution (Lambert 1989). ADePT Health Financing applies the Kakwani index (Kakwani 1977), which is the most widely used summary measure of progressivity in both the tax and the health finance literatures (Wagstaff and others 1992, 1999; O'Donnell and others 2005).<sup>3</sup>

The Kakwani index is defined as twice the area between a payment concentration curve and the Lorenz curve and is calculated as  $\pi_K = C - G$ , where  $C$  is the concentration index for health payments and  $G$  is the Gini coefficient of the ability-to-pay variable.<sup>4</sup> The value of  $\pi_K$  ranges from  $-2$  to  $1$ . A negative number indicates regressivity;  $L_H(p)$  lies inside  $L(p)$ . A positive number indicates progressivity;  $L_H(p)$  lies outside  $L(p)$ . In the case of proportionality, the concentration curve lies on top of the Lorenz curve and the index is  $0$ . The index could also be  $0$  if the curves were to cross and positive and negative differences between them cancel one another. Given this, it is important to use the Kakwani index, or any summary measure of progressivity, as a supplement to, and not a replacement for, the more general graphical analysis.

## Note 20: Progressivity of Overall Health Financing

The progressivity of health financing in total can be measured by a weighted average of the Kakwani indexes for the sources of finance, where weights are equal to the proportion of total payments accounted for by each source. Thus, overall progressivity depends both on the progressivity of the different sources of finance and on the proportion of revenue collected from each of these sources. Ideally, the macro weights should come from the National Health Account (NHA). It is unlikely, however, that all sources of finance that are identified at the aggregate level can be allocated down to the household level from the survey data. Assumptions must be made about the distribution of sources of finance that cannot be estimated. Their distributional burden may be assumed to resemble that of some other source of payment. For example, corporate taxes may be assumed to be distributed as income taxes. In this case, we say that the missing payment distribution has been allocated. Alternatively, we may simply assume that the missing payment is distributed as the weighted average of all the revenues that have been identified. We refer to this as ventilation. Best practice is to make such assumptions explicit and to conduct extensive sensitivity analysis.

**Note 21: Decomposing Redistributive Effect**

One way of measuring the redistributive effect of any compulsory payment on the distribution of incomes is to compare inequality in prepayment incomes—as measured by, for instance, the Gini coefficient—with inequality in postpayment incomes (Lambert 1989). The redistributive impact can be defined as the reduction in the Gini coefficient caused by the payment. Thus,

$$RE = G^X - G^{X-P}, \quad (13.10)$$

where  $G^X$  and  $G^{X-P}$  are the prepayment and postpayment Gini coefficients, respectively;  $X$  denotes prepayment income or, more generally, some measure of ability to pay; and  $P$  denotes the payment. Aronson, Johnson, and Lambert (1994) have shown that this difference can be written as

$$RE = V - H - R, \quad (13.11)$$

where  $V$  is vertical redistribution,  $H$  is horizontal inequity, and  $R$  is the degree of reranking. Because there are few households in any sample with exactly the same prepayment income, one needs to create artificial groups of prepayment equals, within intervals of prepayment income, to distinguish and compute the components of equation 13.11. The vertical redistribution component, which represents the redistribution that would arise if there were horizontal equity in payments, can then be defined as

$$V = G^X - G^0, \quad (13.12)$$

where  $G^0$  is the between-groups Gini coefficient for postpayment income. This can be computed by replacing all postpayment incomes with their group means.  $V$  itself can be decomposed into a payment rate effect and a progressivity effect,

$$V = \left( \frac{g}{1-g} \right) K_E, \quad (13.13)$$

where  $g$  is the sample average payment rate (as a proportion of income) and  $K_E$  is the Kakwani index of payments that would arise if there were horizontal equity in health care payments. It is computed as the difference between the between-groups concentration index for payments and  $G^X$ . In effect, the vertical redistribution generated by a given level of progressivity is “scaled” by the average rate  $g$ .

Horizontal inequity is measured by the weighted sum of the group (j)–specific postpayment Gini coefficients,  $(G_j^{X-P})$ , where weights are given by the product of the group’s population share and its postpayment income share ( $\alpha_j$ ):

$$H = \sum_j \alpha_j G_j^{X-P}. \quad (13.14)$$

Because the Gini coefficient for each group of prepayment equals is nonnegative,  $H$  is also nonnegative. Because it is subtracted in equation 13.11, horizontal inequity can only reduce redistribution, not increase it. This simply implies that any horizontal inequity will always make a postpayment distribution of incomes more unequal than it would have been in its absence.

Finally,  $R$  captures the extent of reranking of households that occurs in the move from the prepayment to the postpayment distribution of income. It is measured by

$$R = G^{X-P} - C^{X-P}, \quad (13.15)$$

where  $C^{X-P}$  is a postpayment income concentration index that is obtained by first ranking households by their prepayment incomes and then, within each group of prepayment “equals,” by their postpayment income. Again  $R$  cannot be negative, because the concentration curve of postpayment income cannot lie below the Lorenz curve of postpayment income. The two curves coincide (and the two indexes are equal) if no reranking occurs.

All in all, the total redistributive effect can be decomposed into four components: an average rate effect ( $g$ ), the departure-from-proportionality or progressivity effect ( $K_E$ ), a horizontal inequity effect ( $H$ ), and a reranking effect ( $R$ ). Practical execution of this decomposition requires an arbitrary choice of income intervals to define “equals.” Although this choice will not affect the total  $H + R$ , it will affect the relative magnitudes of  $H$  and  $R$ . In general, the larger the income intervals, the greater is the estimate of horizontal inequity and the smaller is the estimate of reranking (Aronson, Johnson, and Lambert 1994). That makes the distinction between  $H$  and  $R$  rather uninteresting in applications.<sup>5</sup> More interesting are the quantification of the vertical redistribution ( $V$ ), both in absolute magnitude and relative to the total redistributive effect, and its separation into the average rate and progressivity effects. van Doorslaer and others (1999) decompose the redistributive effect of health finance for 12 Organisation for Economic Co-operation and Development countries.

### Note 22: Redistributive Effect and Economic Welfare

When health care payments are made voluntarily, they do not have a redistributive effect on economic welfare. Payments are made directly in return for a product—health care. It would not make sense to consider the welfare-reducing effect of the payments made, while ignoring the welfare-increasing effect of the health care consumption deriving from those payments. This begs the question of the extent to which out-of-pocket payments for health care should be considered voluntary. It might be argued that the moral compulsion to purchase vital health care for a relative is no less strong than the legal compulsion to pay taxes. But in most instances, there is discretion in the purchase of health care in response to a health problem.

### Notes

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1. The figure is basically the cumulative density function for the reciprocal of the health payments budget share with the axes reversed.
2. For more detail on stochastic dominance, see O'Donnell and others (2008, ch. 7).
3. For other approaches to the measurement of progressivity, see Lambert (1989).
4. The concentration index is presented in great detail in the technical notes presented in chapter 7.
5. See Duclos, Jalbert, and Araar (2003) for an alternative approach that avoids this limitation and Bilger (2008) for an application of this method to health finance analysis.

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#### ECO-AUDIT

### *Environmental Benefits Statement*

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Two key policy goals in the health sector are equity and financial protection. New methods, data, and powerful computers have led to a surge of interest in quantitative analysis that permits the monitoring of progress toward these goals, as well as comparisons across countries. ADePT is a new computer program that streamlines and automates such work, ensuring that the results are genuinely comparable and allowing them to be produced with a minimum of programming skills.

This book provides a step-by-step guide to the use of ADePT for the quantitative analysis of equity and financial protection in the health sector. It also elucidates the concepts and methods used by the software and supplies more-detailed, technical explanations. The book is geared to practitioners, researchers, students, and teachers who have some knowledge of quantitative techniques and the manipulation of household data using such programs as SPSS or Stata.

“During the past 20 years, an increasingly standardized set of tools have been developed to analyze equity in health outcomes and health financing. Hitherto, the application of these analytical methods has remained the province of health economists and statisticians. This book and the accompanying software democratize the conduct of such analyses, offering an easily accessible guide to equity analysis in health without requiring sophisticated data analysis skills.”

**Sara Bennett**, *Associate Professor, Department of International Health, Bloomberg School of Public Health, Johns Hopkins University, Baltimore, Maryland, United States*

“As the international health community becomes increasingly focused on monitoring the impact of universal coverage initiatives, ADePT Health will help make the standard techniques more accessible to policy makers and analysts, increase the comparability of health equity and financial protection measures, and aid in generating the evidence needed to support policy.”

**Kara Hanson**, *Reader in Health System Economics, Health Policy Unit, London School of Hygiene and Tropical Medicine, United Kingdom*

“The ADePT software and manual make it possible for researchers without extensive statistical training to perform a range of analyses that will provide an important evidence base for introducing universal coverage reforms and for monitoring if these reforms are achieving their objectives. The ADePT initiative is an exciting and timely development that will enable researchers in low- and middle-income (as well as high-income) countries to undertake health and health system equity analyses that would previously have been lengthy and extremely resource intensive.”

**Di McIntyre**, *Professor, School of Public Health and Family Medicine, University of Cape Town, South Africa*



Streamlined Analysis with ADePT Software is a new series that provides academics, students, and policy practitioners with a theoretical foundation, practical guidelines, and software tools for applied analysis in various areas of economic research. ADePT Platform is a software package developed in the research department of the World Bank (see [www.worldbank.org/adept](http://www.worldbank.org/adept)). The series examines such topics as sector performance and inequality in education, the effectiveness of social transfers, labor market conditions, the effects of macroeconomic shocks on income distribution and labor market outcomes, child anthropometrics, and gender inequalities.

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