Module 1b: Inequalities and inequities in health and health care utilization

Decomposition, standardization, and inequity

This presentation was prepared by Adam Wagstaff, Caryn Bredenkamp and Sarah Bales
The basic idea
The basic idea

• Inequalities in outcomes (i.e. health or utilization) reflect inequalities in the determinants of outcomes

• This key point allows us to think about two (related) things:
  – How far inequalities are justifiable or unjustifiable (i.e. inequitable); and
  – The relative importance of (inequalities in) different determinants in explaining outcome inequities
Let’s get measuring!
Distinguishing between justifiable and unjustifiable determinants

<table>
<thead>
<tr>
<th>Justifiable determinants ('standardizing' variables) – the X’s</th>
<th>Health outcomes</th>
<th>Utilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, gender</td>
<td>Age, gender</td>
<td>Need for health care, age, gender</td>
</tr>
</tbody>
</table>

| Unjustifiable determinants – the Z’s                          | Income, health insurance status, place of residence | Income, health insurance status, place of residence |

You might be unsure whether a variable is an X (justified) or a Z (unjustified). Don’t worry! ADePT makes it easy to see how your conclusions change depending which way you jump!
Decomposing inequalities—what we’d like to do

Total inequality = Justifiable inequality + Unjustifiable inequality, i.e. inequity

Education, Income, Insurance, Place of residence, Other sources of inequity

Age, gender, etc.
How to do it—in words

• We measure inequality via the concentration index (CI). (Remember this is negative when the outcome is more concentrated among the poor.)

• We assume the outcome (y) is linked to the X’s and the Z’s by a linear regression

• We can then show that the CI for y is linearly related to the CI’s of the X’s and Z’s, where the “coefficients” on the CI’s are the elasticities of y with respect to the X’s and Z’s
For any linear model:

\[ y_i = \alpha + \sum_j \beta_j x_{ji} + \sum_k \gamma_k z_{ki} + \varepsilon_i \]

- \(x\)'s are justifiable determinants or ‘standardizing’ variables
- \(z\)'s are unjustifiable determinants

- the concentration index for \(y\) can be written as:

\[ C = \sum_j (\beta_j \bar{x}_j / \mu) C_j + \sum_k (\gamma_k \bar{z}_k / \mu) C_k + GC_{\varepsilon} / \mu \]

Total inequality = Justifiable inequality + Unjustifiable inequality, i.e. inequity
Some key points

- The terms in parentheses \( \beta_x / \mu \) can be thought of as elasticities, indicating the responsiveness of \( y \) to changes in the \( x \) or \( z \).

- The contribution to inequality of \( x \)'s and \( z \)'s (individually and collectively) depends on:
  1. The elasticity of the outcome with respect to the \( x \) or \( z \); and
  2. The degree of inequality in the \( x \) and \( z \) (measured by their concentration indexes \( C_x \) and \( C_z \)).

- So, an \( x \) or \( z \) that’s highly unequal, and has a large elasticity, will be a big part of the explanation of inequality.

\[
C = \sum_j (\beta_j \bar{X}_j / \mu) C_j + \sum_k (\gamma_k \bar{Z}_k / \mu) C_k + GC_{\varepsilon} / \mu
\]
A tricky (but important) point

• Remember that a positive CI means that the variable is more concentrated among the better off, while a negative CI means it’s more concentrated among the poor
• The elasticity can be positive or negative. So can the CI of the determinant
• So, a negative term in the decomposition could be because:
  – The elasticity is negative but the CI positive; or
  – The elasticity is positive but the CI is negative
• And a positive term in the decomposition could be because:
  – Both the elasticity and the CI are positive; or
  – Both the elasticity and the CI are negative
• Bottom line: we need to know the elasticity and the CI of the determinant to make sense of the decomposition results

\[ C = \sum_j (\beta_j \bar{X}_j / \mu)C_j + \sum_k (\gamma_k \bar{Z}_k / \mu)C_k + GC_\varepsilon / \mu \]
The link between decomposition and ‘standardization’

• Epidemiologists use ‘direct’ and ‘indirect’ standardization to adjust observed outcomes for differences between groups in standardizing variables.
• What’s left after standardization we can think of as ‘inequity’.
• We know that standardization can be done through regression.
• A neat result: If we do an indirect standardization, we get precisely the last term in the decomposition.

\[
C = \sum_j (\beta_j \bar{X}_j / \mu)C_j + \sum_k (\gamma_k \bar{Z}_k / \mu)C_k + G\mathcal{C}_\varepsilon / \mu
\]

Justifiable inequality

Unjustifiable inequality, i.e. inequity

Total inequality
How to do it in ADePT?
What ADePT does

• ADePT produces the full decomposition results, allowing the user to:
  – Break down inequalities into justifiable inequalities and inequities
  – And decompose the causes of inequities so the contribution to inequality from each Z can be quantified
  – To facilitate interpretation, ADePT also outputs the elasticities for each X and Z (and their components) and the CI’s of each X and Z
• Finally, ADePT produces a stacked bar chart showing the contribution to inequality from each X and Z
What ADePT asks for

• ADePT asks the user to indicate:
  – The outcome and/or utilization variables
  – The X’s and the Z’s

• You can play with the ADePT output, exploring the sensitivity of the inequity value to putting the variable(s) in the X rather than the Z
ADePT

Poverty
Labor
Gender
Education
Social protection
Inequality
Health
- Health Outcomes
- Health Financing

☐ Don't show this window at startup

WORLD BANK | DECRG
INDIA (WHS)
Datasets | Variables | Data1 | Filter

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Variable label</th>
</tr>
</thead>
<tbody>
<tr>
<td>hhid</td>
<td>Identification</td>
</tr>
<tr>
<td>pweight</td>
<td>Sample weight</td>
</tr>
<tr>
<td>hhsize</td>
<td>Number of household members</td>
</tr>
<tr>
<td>foodexp</td>
<td>Food expenditures in last 4 weeks (Peso)</td>
</tr>
<tr>
<td>healthexp</td>
<td>Health care expenditures in the last 4 weeks (Peso)</td>
</tr>
</tbody>
</table>

Search

Enable only common variables

Main | Determinants of health / utilization | Benefit Incidence Analysis

Determinants of health
- Standardizing (demographic) variables
- Control variables

Determinants of utilization
- Standardizing (need) variables
- Control variables

Health Outcomes
- Tables selected: 5
- Feasible: 14
- Total: 39

Explaining inequalities in health
- 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
- TH6: Decomposition of the concentration index, linear model
- TH7: Decomposition of the concentration index, non-linear model
- Details on the decompositions
- TH8: Fitted linear model
- TH9: Fitted non-linear model
- TH10: Elasticities, linear model
- TH11: Elasticities, non-linear model
- TH12: Concentration index of the covariates
- TH13: Decomposition of concentration index for health outcomes
- TH14: Decomposition of concentration index for health outcomes

For all tables
- Standard errors (slow)
- Frequencies

Table description and if-condition | ADePT system messages

Data Report presents information on variables selected for the analysis, both non-missing values, mean, minimum, maximum, percentiles, number of missing values, and the mean of each variable. The statistics are generated for variables in every dataset loaded.
Table H3: Health inequality, unstandardized

<table>
<thead>
<tr>
<th>Quintiles of scores for asset index</th>
<th>Low quintile</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Highest quintile</th>
<th>Total</th>
<th>Standard concentration index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quintile</td>
<td>0.035</td>
<td>0.030</td>
<td>0.013</td>
<td>0.017</td>
<td>0.008</td>
<td>0.021</td>
<td>-0.278</td>
</tr>
<tr>
<td>Quintile</td>
<td>0.293</td>
<td>0.253</td>
<td>0.243</td>
<td>0.225</td>
<td>0.176</td>
<td>0.238</td>
<td>-0.097</td>
</tr>
<tr>
<td>Quintile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Quintile</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table H5: Health inequality, indirect standardization

<table>
<thead>
<tr>
<th>Quintiles of scores for asset index</th>
<th>Low quintile</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>Highest quintile</th>
<th>Total</th>
<th>Standard concentration index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quintile</td>
<td>0.021</td>
<td>0.012</td>
<td>0.009</td>
<td>0.008</td>
<td>0.006</td>
<td>0.009</td>
<td>-0.264</td>
</tr>
<tr>
<td>Quintile</td>
<td>0.181</td>
<td>0.193</td>
<td>0.182</td>
<td>0.174</td>
<td>0.136</td>
<td>0.167</td>
<td>-0.078</td>
</tr>
</tbody>
</table>

Most of the inequality disfavoring the poor is not due to age and gender differences across wealth groups. Most of it's inequity.

The totals (i.e. overall averages) differ because some cases have missing information in the X's or Z's.
Inequalities in most Z’s work to widen inequalities in health disfavoring the poor. The biggest contributors are inequalities in wealth and education.

Table H6: Decomposition of the concentration index for health outcomes, linear model

<table>
<thead>
<tr>
<th>Standardizing (demographic) variables</th>
<th>symptoms of TB: coughing for more than two weeks &amp; coughing blood</th>
<th>suffer from chest pain (1/0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F3040 F4050 F5060 F60plus M1830 M3040 M4050 M5060 M60plus</td>
<td>-0.039</td>
<td>0.036</td>
</tr>
<tr>
<td>Subtotal</td>
<td>-0.039</td>
<td>0.036</td>
</tr>
<tr>
<td>Control variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>i.education</td>
<td>-0.056</td>
<td>-0.046</td>
</tr>
<tr>
<td>i.Wealthquint</td>
<td>-0.198</td>
<td>-0.029</td>
</tr>
<tr>
<td>insurone</td>
<td>-0.003</td>
<td>-0.001</td>
</tr>
<tr>
<td>urban</td>
<td>-0.049</td>
<td>0.003</td>
</tr>
<tr>
<td>employee</td>
<td>0.060</td>
<td>-0.002</td>
</tr>
</tbody>
</table>
| SELF
| Subtotal | -0.246 | -0.075 |
| Residual : regression error | -0.019 | -0.003 |
| Residual : missing data | 0.026 | -0.054 |
| Inequality (total) | -0.278 | -0.097 |
| Inequity/Unjustified inequality | -0.265 | -0.078 |
Decomposing inequalities graphically

H1 - symptoms of TB: coughing for more than two weeks & coughing blood
H2 - suffer from chest pain (1/0)
Probing to understand the decomposition results

Employment status and TB

<table>
<thead>
<tr>
<th>Employment category*</th>
<th>Elasticity</th>
<th>CI</th>
<th>Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent working as employee (1/0)</td>
<td>-0.278</td>
<td>0.159</td>
<td>-0.044</td>
</tr>
<tr>
<td>Respondent self-employed (1/0)</td>
<td>-0.801</td>
<td>-0.132</td>
<td>0.105</td>
</tr>
<tr>
<td>Respondent working as employer (1/0)</td>
<td>-0.028</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td>0.061</td>
</tr>
</tbody>
</table>

*Omitted category is person not working
Presenting your results to policymakers
Explain the idea behind the decomposition

\[ \text{Total inequality} = \text{Justifiable inequality} + \text{Unjustifiable inequality, i.e. inequity} \]

- Age, gender, etc.
- Education
- Income
- Insurance
- Place of residence
- Other sources of inequity
Show the sources of inequality graphically (e.g. TB)

- Inequality
- Justifiable
- Inequity

Inequity (disfavoring the poor)

- Employment
- Urban
- Insurance
- Wealth
- Education
- Gender
- Age

Inequality

Justifiable inequality
Policy levers

• The decomposition points to two types of policy lever:
  1. Reducing inequalities in determinants (changing the CI’s of the Z’s), e.g. raising education levels among the poor
  2. Reducing the effects of determinants (changing the γ’s on the Z’s), e.g. health education programs that make general education matter less

• Health ministries have greater scope to implement type-2 interventions (e.g. expanding health insurance). And they can lobby other ministries to implement type-1 interventions

• Decomposition results give a sense of how inequalities would change following each type of intervention
  – You can do some rough simulations in the ADePT output, changing the CI’s or the γ’s of the Z’s, and seeing how the CI of the outcome changes
Where to go from here?
Data sources for decomposing inequalities in health and utilization

• Health surveys like the DHS, WHS, MICS typically contain the needed information
• Multipurpose surveys are also useful
Topics in decomposition not covered in other modules but doable in ADePT

• Nonlinear decompositions for categorical and count data on health and utilization—some debate about just how useful these are
• ‘Direct’ standardization—doesn’t drop out of the decomposition, and not clear they are advantages over the ‘indirect’ standardization method which does link to the decomposition
Topics in decomposition not covered in other modules nor doable in ADePT

• Decompositions with distinct living-standards groups, e.g. poor vs. nonpoor
• Oaxaca and related decompositions. These are discussed in *Analyzing Health Equity Using Household Survey Data* and Stata code is available online for the chapter
Related materials

• Guide to methods: Analyzing Health Equity Using Household Survey Data
• ADePT – Health Manual: Health Equity and Financial Protection
• Online video tutorials
• Health Equity and Financial Protection reports (ongoing)
• Health Equity and Financial Protection datasheets (ongoing)
• Book Attacking Inequality in the Health Sector
• Training events