Decomposing Social Indicators Using Distributional Data

Benu Bidani and Martin Ravallion*

Policy Research Department, World Bank

March 1995.

Abstract

Are the poor less healthy? Does public health spending matter more to them? We decompose aggregate health indicators using a random coefficients model in which the aggregates are regressed on the population distribution by sub-groups, taking account of the statistical properties of the error term. This also allows us to test possible determinants of the variation in the underlying sub-group indicators. The approach is implemented with data on health outcomes and poverty measures for 35 developing countries. We find that poor people have appreciably worse health status on average than others, and that differences in public health spending tend to matter more to the poor.

---

* For comments and discussions, the authors are grateful to Alok Bhargava, Gaurav Datt, P.A.V.B. Swamy, and I-Lok Chang. These are the views of the authors and should not be attributed to the World Bank.

1 Introduction

The ability of people to live a long and active life is clearly of the utmost importance to human development.[1] Unfortunately, conventional data sources are often woefully uninformative about how that ability differs amongst people, and is influenced by policy choices. The high level of aggregation in widely-used social indicators is a common problem.[2] It is often the case that one would like to obtain a sub-group decomposition of a social indicator, but that this is unavailable. There are several reasons: lack of survey integration (some surveys get health data, some get incomes, but fewer get both), too small a sample to capture relatively low-frequency events (such as infant death), or simply the lack of access by users to the underlying micro data. The problem is not unique to health data, but it is quite common for such data.

This paper proposes a method for modelling social aggregates and estimating their sub-group decomposition when one has data on the population distribution across those sub-groups. It is not uncommon to have such data (such as measures of poverty or urbanization) and to use it in modelling socio-economic aggregates.[3] The distinctive feature of the method proposed here is that it exploits the identity linking the social aggregate to the population distribution recognizing the statistical properties of the resulting regression model. In implementing the method we provide what appears to be the first estimate of the decomposition of aggregate health indicators into those of "poor" and "non-poor" persons.

The method also offers a tractable framework for modeling the underlying variation in sub-group means; this is of interest in its own right, as well as helping to assure un-biased estimates of the decomposition. Social-sector policies vary considerably across developing countries; such policies may matter to aggregate health outcomes and they may be correlated with differences in the distribution of consumption or income. We focus on the differential effects of public health spending and primary schooling on the health status of poor versus non-poor people. These effects are far from obvious on a priori grounds. Consider public health spending. On the one hand it has been argued that the poor benefit rather little from existing public spending, and that marginal impacts will be on the non-poor.[4] But on the other hand, a private health-care market generally exists side-by-side with public provisioning. Income effects on demand for health and the substitution possibilities between public and private spending can mean that the health of the poor is more affected by changes in public spending than is health of the non-poor.

The following section outlines the method. In section 3 we use it to decompose aggregate health indicators for developing countries. Section 4 discusses the relationship between our results and other recent work. Section 5 offers some conclusions.

2 The model

The problem is to retrieve the means for various sub-groups of a population when one only knows the aggregate indicator and the population distribution across the sub-groups. We treat the latent sub-group values as random coefficients in a regression of the observed aggregates on the distributional data. To begin, consider the following identity:

$$Y_i = \sum_{j=1}^{M} Y_{ij}\, n_{ij} \tag{1}$$

where Y_i is the social indicator (such as life expectancy) for country i, Y_{ij} is the mean indicator for the j'th sub-group in country i, n_{ij} is the population share of sub-group j in i, with $\sum_{j=1}^{M} n_{ij} = 1$ 1, and where j = 1,..,M denotes the number of sub-groups, and i = 1,..,N, denotes the countries. The sub-group indicators Y_{ij} are not observed, but the Y_i's and n_{ij}'s are. We also observe a vector of explanatory variables for country i, X_i and a vector of explanatory variables for group j in country i, Z_{ij}. Let

$$Y_{ij} = \alpha_j + \beta_{j'} X_i + \gamma_{j'} Z_{ij} + \varepsilon_{ij} \qquad (2)$$

which, on substituting into (1), gives the regression:

$$Y_i = \sum_{j=1}^{M} (\alpha_j + \beta_{j'} X_i + \gamma_{j'} Z_{ij}) n_{ij} + u_i \qquad (3)$$

where

$$u_i = \sum_{j=1}^{M} \varepsilon_{ij} n_{ij} \qquad (4)$$

We assume that $E(\varepsilon_{ij}) = 0$[2] and

$$E(\varepsilon_{ij} \cdot \varepsilon_{i'j'}) = \sigma^2 \Delta_{jj'} \quad for\ i = i' \qquad (5)$$

where Δ[3] is an (MxM) matrix (common to all countries) whose $(j\ j')$[4]'th element is $\Delta_{jj'}$[5]. The error u_i in (3) then has a mean of zero and a block diagonal covariance matrix; specifically:

$$\begin{aligned} &E(u_i) = 0 \ \ for\ all\ i \\ &E(u_i^2) = n_{i'} \sigma^2 \Delta n_i = d_{ii} \\ &E(u_i \cdot u_{i'}) = 0 \ \ for\ i \neq i' \end{aligned} \qquad (6)$$

where n_i is a (Mx1) column vector of population shares and the covariance matrix is

$D = diag(d_{11}, d_{22}, ..., d_{nn})$, where d_{ii} is as defined in (6). We thus have a Hildreth-Houck generalized least squares model.[5] The estimation of this model requires knowledge of the covariance matrix, D.

We estimate the model using the Swamy-Tinsley algorithm, as programmed in the Stochastic Coefficient Estimation Program (SCEP) of Chang and Swamy (1993). This program implements a minimum average risk linear estimator for the model outlined above. It uses an iterative procedure, and an initial data-based Δ6 to estimate stable values of β7 and Δ8. The estimation allows for a non-diagonal Δ9.

3 Results for aggregate health indicators

3.1 Regressions

We shall use cross-country data on the distribution of consumption and country aggregates to estimate the differences in health status between the "poor" and "non-poor".[6] In defining these two groups, we use a cut-off point of $60/per person per month (at 1985 purchasing power parity) or $2 per day. This roughly divides the population of the developing world in the poorest two-thirds and the richest third.[7] This choice is arbitrary, and we consider the effects of relaxing it by using an alternative cut-off of $1 per day (roughly the poorest third of the population falls below this). Unless otherwise stated the data are for about 1990. The Appendix gives more detail on the data.

We use three aggregate health indicators: life expectancy at birth (*LEXP*), the infant mortality rate (*IMR*) and the perinatal mortality rate (*PMR*).[8] We also give results for the crude birth rate (*CBR*) which—though not an interesting health indicator in its own right—will be needed in section 3.2 to decompose the infant and perinatal mortality rates. The vector of explanatory variables comprised the per capita consumptions of the poor and non-poor, public health spending per capita, and the gross primary enrollment rate for 1980.[9] For example, the augmented regression for life expectancy takes the form:

$$LEXP = \hat{\alpha}_p .F(2) + \hat{\beta}_p C_p .F(2) + \hat{\gamma}_p PHS.F(2) + \hat{\delta}_p PRIM.F(2) + \hat{\alpha}_n (1 - F(2)) + \hat{\beta}_n C_n (1 - F(2)) + \hat{\gamma}_n PHS (1 - F(2)) + \hat{\delta}_n PRIM (1 - F(2)) + residual \tag{7}$$

where $F(2)$ 10 denotes the proportion of the population living below \$2 per day, C_j 11 is consumption per person of sub-group j=p,n ("poor", "non-poor"), *PHS* 12 is public health spending per capita at the country level, and *PRIM* is the primary enrollment ratio in 1980 for the country. We also tried the female enrollment rate, and we report results for this when it made a difference.

In no case were the sub-group consumption means significant (indeed, the t-ratios were generally well below 1.0). We comment on this in section 4. On dropping the sub-group consumption means, we obtained the results in Table I, which gives results using cut-off points of \$1 and \$2 per day. We shall initially discuss the results for the \$2 cut-off.

The results show that the per capita health spending variable has a positive effect on the life expectancy of the poor, whereas it has no effect on life expectancy for the non-poor. Countries with a higher incidence of basic schooling have higher life expectancy, though this is mainly achieved through improvements in the life expectancy of the poor, rather than the non-poor.[10] (In section 3.2 we examine the elasticities of health indicators for the poor to differences in public health spending and schooling.)

The same basic pattern is evident in the equation for the infant mortality rate. Public health spending and schooling have a significant effect on the health status of the poor, but not the non-poor. In the equation for the perinatal mortality rate, we find that public health spending has a significant effect on the health status of both the poor and non-poor. The effects of schooling on the *PMR* are evident for the poor. Further, in the equation for the *PMR* we obtained an improvement in fit using the female primary enrollment rate (though missing data entail dropping two countries). Hence for this indicator, we report the regressions for both schooling variables.

We checked the robustness of our estimates to a number of changes in data and assumptions:

i) We tested a weighted specification in which the error variance is proportional to the country's population size. The results in Table I were robust to this change. The only notable change was that the effect of public health spending on the non-poor was no longer evident in the equation for the perinatal mortality.

ii) Tanzania appears to be an unusual data point. According to the data, primary enrollment rates in Tanzania increased dramatically over the late 1970's (from 70% in 1978 to 104% in 1980) and then gradually fell (to about 63% in 1990). The increase in the late 1970's corresponds to a government policy to promote basic education. However, since this increase was so large, we also re-estimated excluding Tanzania to check robustness. Our results showed an even greater effect of primary school enrollments for the poor. The only other notable change was that the effect of health spending on the *PMR* of the non-poor disappeared.

iii) One change that does make a difference is using a lower cut-off point; this is not surprising since it changes the definition of the sub-groups. Public health spending has a larger impact on life expectancy and infant/perinatal mortality for those below $1 per day than for $2 (Table I). Standard errors are also higher, though the effects can still be considered significant for the poor. Public health spending still has no significant effect on the health indicators of the non-poor for all the social indicators. But now we find that the higher gross primary enrollment rate has a significant impact on health status of the non-poor for all indicators. Furthermore, the primary enrollment rate has no impact for those living under a $1 per day, in contrast to $2. These differences with the results for the $2 cut-off presumably reflect impacts of schooling on health amongst those living between $1 and $2 per day.

3.2 *Decomposition of aggregate indicators*

Table I also gives the implied average health indicators for the poor and non-poor. These are evaluated at the population weighted means of X_i, where the weights for the poor (non-poor) are the fraction of the country's poor (non-poor) people to the total population of the poor (non-poor) in these 35 countries.[11] For example, the estimated average life expectancy for sub-group j is:

$$LEXP_j = \alpha_j + \gamma_j \overline{PHS_j} + \delta_j \overline{PRIM_j} \qquad (8)$$

where

$$\overline{PHS_j} = \sum_i \frac{n_{ij} POP_i}{\sum_i n_{ij} POP_i} PHS_i$$

with $\overline{PRIM_j}$ 13 similarly defined, and where POP_i is the population of country i.

Note that both the infant and perinatal mortality rates are expressed as a proportion of the number of live births—not per capita—so an adjustment is needed. For this purpose we also give the decomposition of the crude birth rate (based on the regression in Table I). The adjusted *IMR* for the poor (non-poor) is obtained by multiplying the unadjusted (regression-based) estimate by the ratio of the overall birth rate to the estimated birth rate of the poor (non-poor).[12]

The estimated health indicators for the poor are appreciably worse than for the non-poor. Those living under $2 per day can expect to live 9.4 years less, and their children are 53% more likely to die before reaching one year of age, as those above this figure. The proportionate difference in perinatal mortality is lower, though poor children are still more likely to die around the time of birth.

We re-estimated the decomposition by dropping the public health spending and schooling variables—only regressing the social indicators on the fraction of the population below and above $2 per day. This specification generally implied a larger divergence between health indicators for the poor and non-poor, though it could well give biased results due to the existence of omitted variables correlated with the distribution of consumption.[13]

Estimating the underlying sub-group means at the unweighted means of the explanatory variables also changed the decomposition, though this time the difference between poor and non-poor fell. Table II compares weighted and unweighted means using the $2 cut-off point. For example, while we find a 9 year difference in life expectancies using the weighted means, this falls to about four years when un-weighted. This is attributable in large part to the difference between weighted and unweighted means of public health spending per person (the weighted mean is $28 per person per year, while the unweighted mean is $55).

Table III gives the implied elasticities of the health indicators of those living below $2 per month at mean points. We give results with and without the population weights. At the population-weighted means, life expectancy of the poor responds to public health spending with an elasticity of less than 0.1, while the infant and perinatal mortality rates respond with elasticities of about -0.2. The unweighted elasticities are higher, particularly for infant mortality, for which unweighted means respond with an elasticity of about -0.5. These are point elasticities and (as can be seen from the comparison of weighted and unweighted means) they rise with public spending or using the lower cut-off. Nonetheless, these elasticities do suggest that quite large increases in public health spending may be needed to bridge the gap between health status of the poor and non-poor.

4 Antecedents in the literature

While there is a large literature on the cross-country relationship between social indicators and average income, less attention has been given to the relationship with the distribution of income. We review some exceptions.

Anand and Ravallion (1993) regress various health indicators against both a measure of poverty and public health spending, and (like us) find that both are significant. The data set we have used here is larger (35 countries rather than 22) and all of the countries common to both have had their data up-dated for the present study; thus they are two independent data sets. This adds strength to the conclusion from both studies that both poverty and public health spending matter to social indicators.

Anand and Ravallion also found that average income (the most commonly identified "proximate determinant" of variation in social indicators) is insignificant once one controls for differences in poverty incidence and public health spending.[14] This is also confirmed by our study; if the coefficients on mean consumptions of the poor and no-poor in equation (7) were found to be positive and equal then average consumption per person would emerge as a separate determinant of health outcomes—but our results suggested that neither coefficient is significantly different from zero.

However, because the Anand-Ravallion specification does not exploit the identity linking the aggregates to the sub-group means it does not allow them to retrieve estimates of the decomposition, or of how public health spending might differentially affect health outcomes for the poor versus the non-poor. We find that the Anand-Ravallion conclusion that public health spending is associated with better health indicators should be qualified: cross-country differences in public health spending matter much more to the health outcomes of poor people. This suggests that the non-poor are better able to protect themselves from deficiencies in public provisioning by relying on private health care.

Waldmann (1992) regresses infant mortality on mean income of the poorest 20%, the mean income of the middle 75% (with both these variables adjusted to preserve the purchasing power parity of monetary units), and the income share of the richest 5%. Interestingly, the latter variable has a <u>positive</u> sign and is statistically significant. This leads Waldmann to question the Pareto criterion as a basis for social welfare comparisons; it appears that the rich could be made better off in terms of incomes, with the poor no worse off, and yet an important criterion of social well-being would show a deterioration.

Like Anand-Ravallion, Waldmann's specification is not consistent with the accounting identity linking sub-group indicators to the observed aggregate. A derivation consistent with that identity, under the assumption that each sub-group's indicator is a function of its own mean income, would imply that it should not be the income share of the rich, but their mean income on the right-hand side.[15] One might also question whether the mean of the poorest 20% will pick up the (large) differences in the prevalence of absolute poverty across countries. The risk is then that Waldmann's specification may confound the effects of differences in absolute levels with differences in inequality; the "perverse" sign on the share of the rich may be because that variable is acting as a proxy for the way inequality is influencing the prevalence of absolute poverty and (hence) infant mortality.

Mention should also be made of another approach to incorporating distributional effects. This entails regressing the mean social indicator on mean income, but adding a measure of income inequality.[16] This method does not, however, deliver a decomposition of the sub-group means, or identify impacts of other variables on those means.

One issue ignored here is the appropriate functional form for social indicators in all such models, recognizing that these are bounded variables.[17] There is a quite fundamental aggregation problem here: we only observe the mean of the untransformed indicator. Past practice of transforming the social indicator in some seemingly plausible way,[18] and regressing on other (possibly also transformed) variables is an ad hoc solution, potentially inconsistent with the identity linking the observed aggregate to its sub-group decomposition. Yet certain nonlinearities are plausible. We do not have a solution to this problem.

5 Conclusions

We have addressed two questions often asked about widely used country-level indicators of human development: How different are health indicators between the poor and non-poor? What role do differences in public health spending and schooling play? A random coefficients model was estimated, regressing aggregate life expectancy and infant/perinatal mortality rates across 35 countries against data on the distribution of consumption per person, allowing for differential impacts of public health spending and primary schooling. Estimates of the sub-group means were then retrieved.

The results suggest that those living under $2 per day can expect to live 9 years less on average than the rest, and that their children are 50% more likely to die before their first birthday. Thus the incidence of consumption poverty is an important determinant of aggregate health outcomes. Cross-country differences in public health spending and primary school enrollment also matter, though far more to explaining the cross-country differences in health status of the poor than of the non-poor. The better-off appear to be protected from those differences, presumably because they are in a better position to substitute private for public health spending. This finding reinforces efforts to protect public spending on basic health and education during times of fiscal contraction; not doing so could entail large costs to poor people.

Appendix: Data sources

The data on aggregate health indicators are from World Bank (1993) which is probably the most reliable compilation of such data currently available. The public health spending data are from the same source and are for 1990. The data on primary school enrollment rates are from World Bank (1983) and are for 1980.

The distributional data are from Chen, Datt and Ravallion (1993).[19] All of the primary data sets used are nationally representative household surveys. In all cases, calculations have been from the primary data source (detailed tabulations or household level data), rather than relying on existing estimates. Household consumption expenditure per person is taken to be the preferred indicator of individual living standard. Some surveys use expenditure and some use income per person; for the income-based surveys, the mean has been re-scaled according to national-accounts data on the average propensity to consume. The precise survey dates vary, but the average is about 1989 and the range is 1981 to 1991. The 35 countries are: Algeria, Bangladesh, Bolivia, Brazil, Chile, China, Colombia, Cote d'Ivoire, Dominican Republic, Ethiopia, Ghana, Guatemala, Honduras, India, Indonesia, Jordan, Kenya, Malaysia, Mexico, Morocco, Nepal, Pakistan, Peru, Philippines, Rwanda, Sri Lanka, Tanzania, Thailand, Tunisia, Uganda, Venezuela, Zimbabwe, Hungary, Poland and Yugoslavia. Not all available distributional data sets for the 1980s have been included; several considerations with regard to quality and comparability have guided the selection, as discussed in Chen et al., (1993). An important consideration has been whether the household survey had national-level coverage. Other considerations related to the quality of the data available.

A difficult issue is achieving comparability of currencies across countries. The

International Comparisons Project (ICP) of the U.N. has helped by facilitating the construction of the implicit exchange rates which assure purchasing power parity (PPP) [Summers and Heston (1991)].[20] Though designed for comparing national accounts, the PPP rates also appear to be the best available method of setting internationally comparable poverty lines, and they have been widely used for this purpose; for further discussion see Ravallion et al., (1991). The countries of Eastern/Central Europe and the ex-USSR pose a number of problems. While there are a good deal of distributional data now available, PPP rates are either unavailable or unreliable. Data for Eastern Europe are included when the PPP rates are available from Summers and Heston (1991).

Notes

1. Writings on this topic from various perspectives include World Bank (1980, 1990, 1993), Streeten et al. (1981), Sen (1981, 1985), Drèze and Sen (1989), UNDP (1990), Dasgupta (1993), Kakwani (1993), Anand and Ravallion (1993) and Bhargava (1994).

2. Some efforts to measure "human development" have gone even further by aggregating across multiple socio-economic indicators each one of which is an average for an entire country; both steps entail a potentially large loss of useful information. (The specific way in which the aggregation is done is another issue.)

3. For health indicators see Prescott and Jamison (1985), Waldmann (1992), and Anand and Ravallion (1993). Later we comment on these papers in greater detail.

4. As a stylized fact this is questionable; for a counter-example see van de Walle (1994). For further discussion and references see Lipton and Ravallion (1994, section 6.4).

5. See Hildreth and Houck (1968). For further discussion and other applications see Griffiths (1972), Singh et al., (1976), Swamy and Tinsley (1980), Hoque (1991), and Lass and Gempeshaw (1992).

6. There are other applications. For example, one may want to decompose the aggregate indicator into means for each of urban and rural areas, as in the Prescott and Jamison (1985) study of the regional differences in mortality rates and health-service availability in China. While the application and econometric method is different, it is clear that the Prescott-Jamison problem is formally similar to that addressed here. See Ravallion (1995) for further discussion of

this application.

7. Chen et al. (1993) estimate that 65% of the population of their data set of 40 countries consumed less than $60 per month in 1990.

8. The infant mortality rate is the number of children who die before reaching one year of age per 1000 live births. The perinatal rate refers to late fetal (after seven months) deaths plus deaths within the first week.

9. This is a plausible lag. We also tried the current primary enrollment rates (around 1990). These were more significant, though there may be a simultaneity bias.

10. Results using the female enrollment rates were virtually the same in the life expectancy regression; hence we do not report these.

11. We are grateful to a referee for this suggestion.

12. For example, the coefficient for sub-group j in the IMR equations is $IMR_j\Theta_j$ where Θ_j is the ratio of the birth-rate of sub-group j to the average birth-rate in the population. The estimate of Θ_j is obtained from the birth-rate equation.

13. Ravallion (1995) presents some counter-factual experiments in which the decomposition method was performed on data where the actual values were known. Regressing on only the distributional data gave quite biased results. Augmented regressions performed much better.

14. That does not, of course, mean that growth in average income is irrelevant to aggregate

health outcomes—rather it means that a higher average income only matters in so far as it either reduces poverty or leads to higher social spending.

15. Waldmann (1992, footnote 5) remarks that this specification was tried but made little difference.

16. See, for example, Ravallion (1992) on undernutrition by region in Indonesia. A similar practice can found in some of the literature on modelling aggregate economic variables, such as consumer demands (as in Blundell et al., 1993; for a survey see Stoker, 1993).

17. Anand and Ravallion discuss this issue briefly and give references; also see Kakwani (1993).

18. For example, taking the log of (say) 80 years minus mean life expectancy as used by Anand and Ravallion (1993).

19. There have been compilations of independent estimates of poverty measures by country, such as in World Bank (1992), UNDP (1991), and for the ILO by Tabatabai and Fouad (1993). However, the comparability of these estimates (both between countries and over time) is questionable.

20. The PPP rate for a country is given by the value of the mean outputs of that country evaluated at domestic prices relative to their value at the (output-weighted) mean international prices. The latter in turn depend on the PPP rates, and so a set of simultaneous equations are solved to obtain the PPP rates (Kravis et al., 1982). The main empirical problem is obtaining a

consistent set of prices for goods and services for all countries.

References

Anand, Sudhir, and Martin Ravallion, 1993, Human Development in Poor Countries: On the Role of Private Incomes and Public Services, Journal of Economic Perspectives, 7(Winter): 133-150.

Bhargava, Alok, 1994, A Longitudinal Analysis of Infant and Child Mortality Rates in Developing Countries, mimeo, Department of Economics, University of Houston.

Blundell, Richard, Panos Pashardes, and Guglielmo Weber, 1993, What do we Learn about Consumer Demand Patterns from Micro Data?, American Economic Review, 83(3): 570-97.

Chang, I-Lok, and P.A.V.B. Swamy, 1993, Stochastic Coefficients Estimation Program (SCEP): A User's Guide.

Chen, Shaohua, Gaurav Datt, and Martin Ravallion, 1993, Is Poverty Increasingin the Developing World?, Policy Research Working Paper 1146, World Bank.

Dasgupta, Partha, 1993, An Inquiry into Well-Being and Destitution, Oxford: Oxford University Press.

Drèze, Jean and Amartya Sen, 1989, Hunger and Public Action, Oxford: Oxford University Press.

Griffiths, W.E, 1972, Estimating Actual Response Coefficients in the Hildreth-Houck Random Coefficient Model, Journal of the American Statistical Association, 67, 633-635.

Hildreth, C. and J.P. Houck, 1968, Some Estimators for a Linear Model with Random Coefficients, Journal of the American Statistical Association, 63, 584-595.

Hoque, Asraul, 1991, An Application and Test for a Random Coefficient Model in Bangladesh Agriculture, Journal of Applied Econometrics, 6, 77-90.

Kakwani, N., 1993, Performance in Living Standards: An International Comparison, Journal of Development Economics 41:307-336.

Kravis, I. B., A. Heston, and R. Summers, 1982, World Product and Income: International Comparisons of Real Gross Product, Baltimore: John Hopkins.

Lass, Daniel A. and Conrado M. Gempeshaw II, 1992, The Supply of Off-Farm Labor: A Random Coefficients Approach, American Journal of Agricultural Economics, 400-411.

Lipton, Michael and Martin Ravallion, 1994, Poverty and Policy, in Jere Behrman and T.N. Srinivasan (eds) Handbook of Development Economics Volume 3 Amsterdam: North-Holland, forthcoming.

Prescott, Nicholas, and Dean Jamison, 1985, The Distribution and Impact of Health Resource Availability in China, International Journal of Health Planning and Management 1: 45-56.

Ravallion, Martin, 1992, Does Undernutrition Respond to Incomes and Prices? Dominance Tests for Indonesia. World Bank Economic Review 6(1): 109-124.

________________, 1995, How Well Can Methodology Substitute for Data? Five Experiments in Poverty Analysis, mimeo, Poverty and Human Resources Division, Policy Research Department, World bank.

Ravallion, Martin, Gaurav Datt, and Dominique van de Walle, 1991, Quantifying Absolute Poverty in the Developing World, Review of Income and Wealth 37:345-361.

Sen, Amartya, 1981, Public Action and the Quality of Life in Developing Countries, OxfordBulletin of Economics and Statistics 43(4): 287-319.

____________, 1985, Commodities and Capabilities. Amsterdam: North-Holland.

Singh, B., A.L. Nagar, N.K. Choudhury, and B. Raj, 1976, On the Estimation of Structural

Change: A Generalization of the Random Coefficients Regression Model, International Economic Review, 17, 340-361.

Stoker, Thomas M., 1993, Empirical Approaches to the Problem of Aggregation Over Individuals, Journal of Economic Literature 31(4): 1827-1874.

Streeten, Paul, Shahid Javed Burki, Mahbub ul Haq, Norman Hicks, and Frances Stewart, 1981, First Things First: Meeting Basic Needs in Developing Countries. New York: Oxford University Press.

Summers, Robert and Alan Heston, 1991, The Penn World Table (Mark 5): an Extended Set of International Comparisons, 1950-1988, Quarterly Journal of Economics 106:327-368.

Swamy, P.A.V.B. and P.A. Tinsley, 1980, Linear Prediction and Estimation Methods for Regression Methods with Stationary Stochastic Coefficients, Journal of Econometrics, 12, 103-42.

Tabatabai, Hamid with Manal Fouad, 1993, The Incidence of Poverty in DevelopingCountries. An ILO Compendium of Data. Geneva: International Labour Office.

United Nations Development Program (UNDP), 1990, Human Development Report New York: Oxford University Press.

van de Walle, Dominique, 1994, The Distribution of Subsidies through Public Health Services in Indonesia, 1978-87, The World Bank Economic Review, 8, 279-309.

Waldmann, Robert, 1992, Income Distribution and Infant Mortality, Quarterly Journalof Economics 107: 1283-1302.

World Bank, 1980, 1983, 1990, 1992, 1993 World Development Report. New York: Oxford University Press for the World Bank.

_____ , 1992, Social Indicators of Development 1991-92. Baltimore: Johns Hopkins University Press for the World Bank.

Table I: Cross-country regressions for aggregate health indicators

	Life expectancy		Crude birth rate		Infant mortality		Perinatal Mortality (1)		Perinatal mortality (2)	
Cut-off (z) $/day	z = $2	z = $1	z = $2	z = $1	z = $2	z = $1	z = $2	z = $1	z = $2	z = $1
Fraction of population below z (F(z))	37.03 (6.84)	42.81 (11.92)	57.19 (12.25)	46.52 (23.91)	175.91 (31.84)	146.44 (55.51)	129.52 (27.56)	84.05 (40.70)	113.27 (18.06)	105.07 (31.45)
Fraction of population over z (1 - F(z))	57.83 (8.57)	43.79 (5.99)	47.06 (18.11)	56.41 (10.47)	121.78 (48.28)	165.97 (29.10)	38.89 (28.28)	99.77 (20.96)	51.71 (19.46)	84.38 (14.17)
Public health spending per capita x F(z)	0.15 (0.04)	0.36 (0.11)	-0.11 (0.08)	-0.19 (0.19)	-0.52 (0.22)	-1.11 (0.51)	-0.27 (0.15)	-0.98 (0.37)	-0.29 (0.14)	-0.79 (0.36)
Public health spending* x (1 - F(z))	0.015 (0.01)	0.03 (0.02)	-0.06 (0.03)	-0.05 (0.03)	-0.09 (0.09)	-0.12 (0.08)	-0.10 (0.04)	-0.06 (0.06)	-0.08 (0.04)	-0.06 (0.06)
Gross primary enrollment rate (1980) x F(z)	0.18 (0.08)	0.03 (0.15)	-0.20 (0.15)	0.01 (0.29)	-0.95 (0.38)	-0.33 (0.69)	-0.74 (0.32)	0.18 (0.51)	-0.59 (0.24)	-0.14 (0.44)
Gross primary enrollment rate x (1 - F(z))	0.08 (0.09)	0.20 (0.07)	-0.15 (0.19)	-0.26 (0.12)	-0.76 (0.50)	-1.14 (0.33)	0.03 (0.28)	-0.62 (0.24)	-0.13 (0.21)	-0.49 (0.18)
Squared correlation coefficient between actual and predicted values	0.74	0.74	0.54	0.56	0.72	0.73	0.63	0.67	0.70	0.71
Mean (poor)	57.51 (1.86)	53.53 (3.04)	36.17 (3.45)	43.17 (5.90)	69.13 (8.25)	69.85 (10.83)	50.51 (6.62)	58.34 (7.90)	54.09 (5.72)	58.36 (7.50)
Mean (non-poor)	66.89 (2.23)	64.75 (1.59)	27.61 (4.80)	27.71 (2.75)	45.17 (15.39)	53.95 (9.16)	44.81 (8.65)	40.76 (6.59)	42.62 (8.42)	43.86 (6.22)

Note: Standard errors in parentheses. Perinatal mortality (2) includes the gross female primary enrollment rate for 1980, instead of the total primary enrollment rate; two countries had to be excluded in this regression because data on female primary enrollment rates were unavailable.

Table II: Estimated mean health indicators for those above and below $2 per day

	Evaluated at unweighted mean of explanatory variables		Evaluated at population weighted means of explanatory variables	
	Mean for poor	Mean for non-poor	Mean for poor	Mean for non-poor
Life expectancy	61.75 (2.15)	65.93 (2.00)	57.51 (1.86)	66.89 (2.23)
Crude birth rate	32.92 (4.18)	29.38 (4.19)	36.17 (3.45)	27.61 (4.80)
Infant mortality rate	57.03 (10.49)	50.30 (11.93)	69.13 (8.25)	45.17 (15.39)
Perinatal mortality rate (1)	44.25 (7.59)	39.13 (7.14)	50.51 (6.62)	44.81 (8.65)
Perinatal mortality rate (2)	45.47 (6.94)	39.22 (6.92)	54.09 (5.72)	42.62 (8.42)

Table III: Elasticities of health indicators for the poor

	Elasticity of social indicator with respect to:			
	Public health spending	Primary school enrollment rate	Public health spending	Primary school enrollment rate
	(Evaluated at unweighted mean)		(Evaluated at population weighted mean)	
Life expectancy	0.13	0.27	0.07	0.28
Crude birth rate	-0.18	-0.56	-0.08	-0.50
Infant mortality rate	-0.50	-1.54	-0.21	-1.24
Perinatal mortality rate (1)	-0.34	-1.54	-0.15	-1.32
Perinatal mortality rate (2)1	-0.36	-1.08	-0.15	-0.85

Note: Elasticities evaluated at estimated mean for the poor (Table II) and the sample averages (weighted or unweighted) of national public health spending per capita and primary enrollment. The unweighted sample mean of health spending in this regression is $55.0 per person per year, while the weighted mean is $ 28.31; the corresponding means for the primary school enrollments are 92.4% and 90.36% (for females they are 84.1% and 78.32%).