

Does reporting heterogeneity bias the measurement of socio-economic inequalities in health?

Teresa Bago d’Uva, University of York

Eddy van Doorslaer, Erasmus University

Maarten Lindeboom, Free University of Amsterdam

Owen O’Donnell, University of Macedonia

Somnath Chatterji, WHO

September 2005

Preliminary and incomplete.

1. INTRODUCTION

Self-reported health is a convenient and valuable instrument that facilitates a multitude of analyses of health in relation to socio-economic characteristics. Inevitably, self-reported health reflects reporting heterogeneity. That is, for a given true but unobserved health state, individuals will report health differently depending upon, for example, conceptions of health, expectations for own health and understanding of the survey questions. In many contexts, such reporting heterogeneity need not be a major concern provided that it is random. Systematic differences in reporting behaviour are more problematic. For example, measurement of inequality in health will be biased if there are systematic differences in the way in which health is reported across the

socio-economic characteristics against which inequality is being assessed. Sen (2002) notes that “there is a strong need for scrutinising statistics on self-reported illness in a social context by taking note of levels of education, availability of medical facilities and public information on illness and remedy”.

Differences in health disparities derived from self-reported and more objective indicators are suggestive of systematic variation in reporting behaviour. One frequently cited example is the tendency for Aboriginals to report better health than the general Australian population (Mathers and Douglas, 1998) despite being seriously disadvantaged according to other more objective health indicators (such as mortality). Such discrepancy in health gradients measured by objective and subjective indicators is even more common in evidence from the developing world. In India, the state of Kerala consistently shows the highest rates of reported morbidity, in spite of having the lowest rates of infant and child mortality (Murray, 1996). Wagstaff (2002) notes that income-related inequalities in objective indicators of ill-health, such as anthropometric measures of malnutrition and mortality, tend to be higher than the ones obtained when health is measured according to subjective indicators of health. Moreover, the use of subjective health measures has led to some perverse gradients in developing countries, indicating that the rich report worse health than the poor (Baker and van der Gaag, 1993). For example, for Brazil, data from the Living Standards Measurement Survey show pro-poor inequality in self-reported (adult) health (Wagstaff, 2001) in spite of the existence of a large pro-rich inequality in the rate of under 5 mortality in this country (Gwatkin et al, 2000).

More formal testing for reporting heterogeneity by socio-economic status has been undertaken in recent studies, albeit not in an exhaustive way, and not for less developed countries. van Doorslaer and Gerdtham (2003) use Swedish data to assess to which extent the ability of self-reported health to predict mortality varies across socio-demographic group. They find that self-reported health is a very strong predictor of

subsequent mortality risk. The relationship varies with demographic and disease characteristics but not by socioeconomic status and therefore measured income-related inequality in health is unlikely to be biased by reporting error. Lindeboom & Van Doorslaer (JHE, 2004) develop a model for individual reporting behaviour, which they apply to Canadian health survey data. Their approach uses the McMaster HUI 3 index (assumed to be a more objective and comprehensive health indicator) and provides a formal test of whether variations in responses to health reflect true health differences or reporting behaviour. The results are consistent with those of Gertham and van Doorslaer, there is evidence of reporting heterogeneity for age and gender, but not for education and income. While this evidence is encouraging, it says nothing about the effect of reporting heterogeneity on the measurement of health inequality in developing countries where differences in conceptions of illness by education and income levels may be greater.

All the studies discussed in the previous paragraph follow the general strategy of testing for socio-economic related reporting heterogeneity through examination of variation in health reporting conditional on some “objective” measure of health. One disadvantage is that objective indicators, for example mortality, may not be available. Less objective indicators, such as health conditions, are more likely to be available but are also self-reported. So, the test might uncover different types of reporting heterogeneity in different indicators rather than differences in reporting relative to a purely objective benchmark. A further disadvantage of using “objective” indicators to test and correct for reporting heterogeneity is that this strips out any socio-economic related variation in self-reported health conditional on the objective indicators. If the self-reported health contains information on true health, conditional on objective indicators, then this is lost. If self-reported health does not contain this additional information, then one might as well examine the relationship between “objective” indicators and socio-economic characteristics from the outset.

Rather than learn about reporting heterogeneity through examination of variation in self-reported health beyond that explained by “objective” indicators, an alternative is to examine variation in the reporting of given health states as represented by hypothetical cases or vignettes (Tandon et al, 2003). Given that the vignettes represent fixed levels of latent health, all the systematic variation in vignette responses can be attributed to reporting behaviour, which can be examined in relation to observed characteristics. Under the assumption that individuals rate the vignettes in the same way as they rate their own health, this approach enables the identification of a measure of health purged of reporting heterogeneity. In this paper, we apply the vignette methodology to data from the three largest Asian countries (Indonesia, India and China) in order to test for systematic differences in reporting of health by gender, age, education and income and to examine to what extent the estimated associations between health and both education and income are sensitive to purging measured health of these systematic reporting differences.

2. DATA - WHO MULTI-COUNTRY SURVEY STUDY

The data used in this paper are taken from the WHO Multi-Country Survey Study on Health and Responsiveness 2000-2001 (WHO-MCS) which covered 71 adult populations in 61 countries. Üstün TB et al (2003) provide a comprehensive report on the goals, design, instrument development and execution of this multi-country study. The study focused on the way in which people report their own health. Individuals were asked to report their levels of health in each of six domains (*mobility, cognition, affect, pain, self-care, usual activities*). In addition, a sub-sample of individuals were asked to rate a set of anchoring vignettes describing fixed ability levels on each health domain. This makes it possible to test and control for heterogeneous health reporting behaviour across populations or socio-demographic groups. Individual assessments of their own health by domain can be calibrated against the vignettes, making it

possible to adjust the responses and achieve comparability.

We use WHO-MCS data for Indonesia (excluding Papua, Aceh and Maluku¹), an Indian state (Andhra Pradesh) and 3 Chinese provinces (Gansu, Henan and Shandong).² The dataset used here results from dropping the individuals with missing observations for the variables representing own health and the socio-demographic variables included in the analysis. Additionally, the individuals that have incomplete information on the vignettes have not been used. The resulting dataset contains 6715 observations for Indonesia, 5124 for India and 6975 for China.

Health variables: own health and vignettes

In addition to reported health in each of the six domains, individuals are asked to assess their overall level of health. The variable SAH (general self-assessed health) results from the question: “In general, would you rate your health today?”, with answers: “Very bad”, “Bad”, “Moderate”, “Good”, “Very Good”. Table 1 presents the distribution of SAH by country.

Table 1

The variables on health by domain are obtained from the questions: “Overall in the last 30 days, how much...”:

- ...distress, sadness or worry did you experience? (*Affect*)
- ... difficulty did you have with concentrating or remembering things? (*Cognition*)
- ... difficulty did you have with moving around? (*Mobility*)

¹These provinces were excluded from the sampling frame due to political reforms and economic crisis.

²In China and India, the study was limited to these areas due to the size of the countries and language barriers.

- ... pain or discomfort did you have? (*Pain*)
- ... difficulty did you have with work or household activities? (*Usual Activities*)

The response categories for the health domains variables are: “Extreme/Cannot do”, “Severe”, “Moderate”, “Mild”, “None”. Table 2 presents the distributions of the self-reported health variables by domain and by country.

The WHO-MCS contains assessments of sets of vignettes for the 6 domains. Each vignette describes a fixed level of difficulty on a given domain. Individuals are asked to evaluate these hypothetical cases in the same way as they evaluate their own health for that domain (i.e., responding to the same question and using the same 5 response categories). For each of the six health domains, a sub-sample of respondents are asked to classify a set of vignettes (6 for *mobility* and *affect*, 7 for *self-care* and *pain* and 8 for *usual activities* and *cognition*). The vignette descriptions for all the domains are presented in the Appendix. The distribution of the vignettes by domain and country are presented in Table 2.

Table 2

Despite representing fixed levels of ability by domain, the vignette ratings show considerable variation, which can be attributed to individual reporting heterogeneity. We exploit this variation to model the cut-points on a latent index of health at which different categories of health are reported as functions of the covariates. We are particularly interested in assessing to what extent the reporting behaviour varies systematically by socio-economic status (income and education) and, ultimately, in estimating the corrected effects of socio-economic status on health by domain.

Socio-demographic variables

From the data, individuals can be characterised by age, sex and socio-economic status (represented by education and household income). In order to allow for a flex-

ible age effect, as well as a more direct interpretation than that given by polynomials, age is represented by categories: 15 to 29 (reference category), 30 to 44 (AGE3044), 45 and 59 (AGE4559) and more than 60 (AGE60). Sex is represented by the dummy variable FEMALE. EDUC measures the number of years of schooling. The variable INCOME represents monthly household income by equivalent adult (in national currencies). This variable was obtained from the information on weekly household income (multiplied by 30.5/7), when available. When information on weekly income was not available, the information on monthly income was used. In the absence of either information on weekly or monthly income, we used annual income divided by 12. Finally, the resulting variable was divided by an equivalence scale (calculated as $(\text{number of adults in household} + 0.5 \times \text{number of children in household})^{0.75}$). Table 3 presents descriptive statistics for the covariates by country. The difference in the education levels across countries is noticeable. The average number of schooling years is particularly low for India.

Table 3

3. ECONOMETRIC MODELS

The data provide categorical indicators of general SAH and domain specific health. Such data are typically modelled by assuming that the observed categorical variable is a discrete representation of an unobserved true level of health, measured on a continuous scale. Formally, the categorical variable is defined as the result of a mapping between latent health and the categorical response categories. Homogenous reporting behaviour corresponds to the assumption that the mapping is constant across individuals. This, together with assumed normality of latent health disturbances, gives the ordered probit model, which has been a popular choice for the analysis of SAH (e.g. Contoyannis et al, 2004). In this case, the threshold levels (or cut-points) of

latent health that determine the transition from one reported category to the next are specified as constant parameters. By contrast, reporting heterogeneity translates into different mappings between the latent variable and the observed categorical variable, i.e. different cut-points. Individuals might attach very different meanings to the labels used for each of the response categories, thus making the observed health variables incomparable, since they do not correspond to the same intervals in the latent health scale. The use of different scales by different individuals has been referred to as response category cut-point shift (e.g. Murray et al 2000) or differential item functioning (King et al, 2004). Given the availability of vignette ratings, the possibility of heterogeneous health reporting behaviour can be accommodated by an extension of the ordered probit model in which reporting behaviour and so the cut-points allowed to depend on observables (Tandon et al, 2003). The separate identification of the effects of the covariates on health and on the cut-points is made possible by the use of vignette ratings, since all the systematic variation in the vignette evaluations is assumed to be attributable to reporting behaviour, thus purging the health effects of reporting heterogeneity.

3.1. Ordered Probit: Homogeneous reporting behaviour

Let y_i , $i = 1, \dots, N$, be a self-reported categorical health measure, which can represent general self-assessed health or a given domain of health. It is assumed that y_i is generated by the latent health variable Y_i^* which is determined by:

$$Y_i^* = Z_i\beta + \varepsilon_i, \quad \varepsilon_i|Z_i \sim N(0, 1) \quad (1)$$

where Z_i is a vector of covariates. Since the latent variable is unobserved and its observed counterpart is categorical, the variance of ε_i , conditional on Z_i , and the

constant term are not identified and are usually set to 1 and 0, respectively.³

The observed categorical variable y_i relates to latent health in the following way:

$$y_i = k \text{ if } \tau^{k-1} \leq Y_i^* \leq \tau^k, \quad (2)$$

for $\tau^0 = -\infty, \tau^5 = \infty, \forall i \text{ \& } k = 1, \dots, 5$

where $\tau^k, k = 1, \dots, 4$ are parameters to be estimated along with β and $\tau_1 < \tau_2 < \tau_3 < \tau_4$. It follows from equations (1) and (2) that the probabilities associated with each of the 5 categories are given by:

$$\Pr[y_i = k] = F(\tau^k - Z_i\beta) - F(\tau^{k-1} - Z_i\beta), \quad \text{for } k = 1, \dots, 5 \quad (3)$$

where $F(\cdot)$ is the cumulative standard normal distribution. The assumption of homogeneous reporting that is inherent to the ordered probit model arises from the constant cut-points τ^k . If this assumption does not hold, in particular, if the cut-points vary according to some of the covariates considered in Z_i , then imposing the restriction that the cut-points are constant will lead to biased estimates for β . This stems from the fact that the estimated β comprises both health effects and reporting effects. However, without additional information, it is not possible to identify the separate effects of Z on the latent variable and the cut-points.

3.2. Hierarchical Ordered Probit (HOPIT): Heterogenous reporting behaviour

The HOPIT model developed by Tandon et al (2003) modifies the ordered probit model, in order to allow for heterogeneous reporting behaviour. This approach makes use of the ratings of anchoring vignettes included in the WHO-MCS, described

³In the results presented in Section 5, these terms are fixed in a different way. In order to ensure comparability between the coefficients of the covariates in the two models, the constant term and the variance in the ordered probit model are set equal to the ones estimated in the extended model.

above, enabling the specification of the cut-points as functions of the covariates. The effects of covariates on the cut-points are identified by the systematic variation of the vignette ratings, assumed to be wholly attributable to reporting bias. The HOPIT model thus disentangles the effects of the covariates on individual own health and on the cut-points, correcting the health effects by accounting for reporting heterogeneity. The model is specified in two parts: one reflecting reporting behaviour and another representing the relationship between health and the observables. The use of vignettes to identify the cut-points and so systematic reporting heterogeneity relies on two assumptions. First, there must be response consistency: individuals classify the hypothetical cases represented by the vignettes in the same way as they rate their own health. That is, the mapping used to translate the perceived latent health of others to reported categories is the same as that governing the correspondence between own latent and reported health. This is essential if we are to learn about how individuals report their own health from how they rate others health. While untestable, the assumption is not unchallengeable. For example, demographic, and possibly inferred social, characteristics of the vignette cases may be taken into account when ratings are made. Further, incentives, such as ill-health conditions for social security entitlement, may influence rating of own health but be irrelevant to the reporting of others health. The second assumption necessary for identification of reporting behaviour via the vignettes is irrelevance of own health. That is, conditional on socio-demographics that influence reporting behaviour, the individual's own latent health does not impact on the way in which she reports the health of others. If this is not the case, then the variation in reporting of the vignettes does not only derive from reporting heterogeneity and it is not possible to separate the reporting behaviour from true health. The assumption would not hold if individuals rate the health of others relative to their own health. For example, someone that cannot climb a flight of stairs might be perceived as moderately immobile by someone

that is confined to a wheelchair but as severely immobile by another that is fully fit.

Reporting behaviour

The first (vignette) component of the HOPIT uses information on the vignette ratings to model the cut-points as functions of covariates. For a given health domain, let Y_{ij}^{v*} be the latent health level of vignette j perceived by for individual i . Given that each vignette j represents a fixed level of ability, any association between the latent level of health Y_{ij}^{v*} and individual characteristics is ruled out. $E[Y_{ij}^{v*}]$ is therefore assumed to depend solely on the corresponding vignette. Formally, it is assumed that Y_{ij}^{v*} is determined by:

$$Y_{ij}^{v*} = J_i \alpha + \varepsilon_{ij}^v, \quad \varepsilon_{ij}^v | J_i \sim N(0, 1) \quad (4)$$

where J_i is a vector of dummies representing the $V - 1$ vignettes.

The observed vignette ratings y_{ij}^v relate to Y_{ij}^{v*} in the following way:

$$\begin{aligned} y_{ij}^v &= k \text{ if } \tau_i^{k-1} \leq Y_{ij}^{v*} \leq \tau_i^k, \\ \text{for } \tau_i^0 &= -\infty, \tau_i^5 = \infty, \forall i, j \text{ \& } k = 1, \dots, 5 \end{aligned} \quad (5)$$

where the cut-points are defined as functions of covariates:

$$\tau_i^k = X \gamma^k, \quad (6)$$

with $\tau_i^1 < \tau_i^2 < \tau_i^3 < \tau_i^4$. In the vignette component of the HOPIT model, the covariates are included only in the cut-points, reflecting the assumption that all the systematic variation in the vignette ratings can be attributed to individual reporting behaviour.

Health equation

Similarly to the ordered probit, the second component of the HOPIT defines the latent level of individual own health, Y_i^{s*} , and the observation mechanism that relates

this latent variable to the observed categorical variable, y_i^s . However, the second component of the HOPIT differs from the ordered probit in that the cut-points are not constant parameters but can vary across individuals, being determined by the vignette component of the model. Identification derives from the response consistency assumption that the cut-points in the own health model are the same as those in the vignette model and the assumption that the reporting on vignette health is not influenced by own latent health. The possibility of fixing the cut-points leads to the specification of the model for individual own health as an interval regression, enabling the identification of the constant term and the variance. The latent level of individual own health is determined by:

$$Y_i^{s*} = Z_i\beta + \varepsilon_i^s, \quad \varepsilon_i^s | Z_i \sim N(0, \sigma^2) \quad (7)$$

where Z_i is a vector of covariates including a constant. The observed categorical variable y_i^s is such that:

$$\begin{aligned} y_i^s &= k \text{ if } \tau_i^{k-1} \leq Y_i^{s*} \leq \tau_i^k, \\ \text{for } \tau_i^0 &= -\infty, \tau_i^5 = \infty, \forall i \text{ \& } k = 1, \dots, 5 \end{aligned} \quad (8)$$

where τ_i^k are as defined in the vignette model.

It is assumed that Y_{ij}^{v*} and Y_i^{s*} are independent for all $i = 1, \dots, N$ and $j = 1, \dots, V$. The probability of observing each of the categories in the vignette responses and self-reported health is determined as in equation (3). Each of these response probabilities enters the log-likelihood function of the HOPIT model, composed by the sum of the log-likelihoods of the two components. The two components are linked through the cut-points, which are driven by the vignettes and imposed on the second (own health) component of the HOPIT. In this study, we are especially concerned with the effects of education and income on own health, corrected by reporting heterogeneity. These are given by the corresponding estimated β s of the HOPIT model. Comparison between

the estimated effects in the ordered probit and the HOPIT models allows assessment of the importance of accounting for reporting heterogeneity.

Test of heterogeneity in reporting behaviour

This framework offers the possibility of testing for heterogeneous reporting behaviour according to the individual characteristics considered. This is done by means of log-likelihood ratio tests of significance of (groups of) covariates in the cut-points. If the estimated coefficients of certain factor, say education, in the cut-points are found to be jointly significant, then the null hypothesis of homogeneity of reporting behaviour across individuals with different levels of education, conditional on the remaining covariates, is rejected.

4. RESULTS

For each of the 6 health domains considered, we estimate ordered probit models and HOPIT models separately by country. Additionally, we estimate ordered probit models for SAH. Individual own latent health (ordered probit, equation (1), and HOPIT, equation (7)) and the cut-points (HOPIT, equation (6)) are defined as functions of the same covariates: FEMALE, AGE3044, AGE4559, AGE60, EDUC and Log(INCOME). The mean health function in the vignette component of the HOPIT includes only indicators of the vignettes. We focus on the reporting and health effects of income and education (conditional on age and sex). Regarding the health effects, we compare what is obtained before and after the adjustment for reporting heterogeneity. In general, expectations of health and tolerance of illness may be influenced by the socio-economic environment as well as demographic characteristics. For example, living within an unhealthy population may lower expectations for health. Good access to effective health care may lower tolerance of illness and disease. For such reasons, the a priori expectation might be that richer individuals have higher stan-

dards regarding health, meaning that they tend to report worse health than poorer individuals, all else equal. If this is the case, then a model that does not account for reporting heterogeneity will underestimate the health effects of income, since these combine a positive (true) effect on health with a negative effect on the reported level of health, conditional on true health. To the extent that income does not fully capture variation in living standards, education might also be correlated with reporting behaviour through poverty and access to health care. But there may also be direct effects of education on conceptions of illness, understanding of disease and knowledge of the effectiveness of health care. It is not immediately clear in which direction such effects will shift the reporting of health. One might expect the better educated to be less tolerant of poor health. On the other hand, the better educated should be better informed of the health of others and able to appreciate their relatively privileged position in the health distribution.

4.1. Reporting behaviour

In general terms, higher health standards or expectations are represented in the HOPIT model by positive shifts in the cut-points. If a certain covariate has positive coefficients across all the cut-points, then it is clear that higher values of that covariate are associated with higher health standards. In this case, the estimated effect of that covariate on health will increase after the HOPIT adjustment for reporting bias. Tables 4 and 5 present the coefficients of EDUC and LOG(INCOME) in the cut-points, for 6 health domains, for India, Indonesia and China.

Tables 4&5

A first look at these results shows some evidence of reporting heterogeneity by income and education. For almost all the domains/countries, income and education influence significantly at least one of the cut-points. It is noticeable that, in some

domains/countries, the cut-point shifts are not always in the same direction. The coefficients of $\text{Log}(\text{INCOME})$, table 4, are always positive for *cognition*, in the case of Indonesia, for *self care* and *usual activities*, in the case of India and for *pain*, *self care* and *affect*, in China. This denotes that richer individuals have higher expectations regarding health in these particular domains/countries, which means that the HOPIT model will estimate greater income effects than the ordered probit model. For the remaining cases, the relationship between income and health standards is not as straightforward, since the cut-point shift by income is not uni-directional. It is therefore not clear in which direction the HOPIT adjustment will operate. Let us focus on the last cut-point, the threshold between the two upper categories. The coefficients of this cut-point determine the probability of being in the upper category, equation (3). A positive coefficient of income in that cut-point means that richer individuals have a lower probability of responding “no difficulties”. They have a higher standard regarding what it means to have no difficulties in the respective health domain. Most of the individuals are concentrated in the upper category for each of the domains, in the 3 countries (table 2). Therefore, one can expect the shift in the upper cut-point to play an important role in the direction of the HOPIT adjustment, even in the cases for which the cut-point shift is not uni-directional. With the exceptions of *self care* for Indonesia, *affect* for India and *mobility* for China (for which the coefficient of income in the last cut-point is non-significantly negative) the coefficient of income in that cut-point is always positive. This allows us to conclude that richer individuals have a lower probability of reporting no difficulties in the respective health domain (except for the 3 cases mention above).

Table 5 shows the results on reporting behaviour according to education level. Except for *pain* in the case of China, EDUC has a negative effect in the last cut-point. More educated people are therefore more likely to report no difficulties in all the health domains for Indonesia and India and for all the domains except for *pain*, in

the case of China. In particular, in the domains of *self care*, *usual activities* and *affect*, for India, and *mobility*, *cognition*, *self care* and *usual activities*, for China, education has a negative impact on all the cut-points, representing an unambiguous association between higher education and lower health standards.

Tests of reporting heterogeneity

Table 6 presents the results of the tests of homogeneous reporting behaviour. Each column includes the p-values of log-likelihood ratio tests of joint significance of the respective (groups of) covariates in the 4 cut-points.

Table 6

Columns (1), (6) and (11) show evidence of cut-point heterogeneity according to at least one of the characteristics considered, except for affect in China. There is evidence of reporting heterogeneity by gender in 4 domains in Indonesia and China and all of the domains in India. There is also evidence of heterogeneity by age groups for some of the domains/countries. Regarding the main focus of this study, the null hypothesis that the cut-points are homogeneous according to income and education is often rejected. In the case of Indonesia, education influences significantly the cut-points in all the domains. Homogeneous reporting by education is also rejected for *pain* and *usual activities*, in the case of India, and *cognition*, *pain*, *self care* and *usual activities*, in the case of China. As to the effect of income on reporting behaviour, there is evidence that this is significant for most of the cases.

4.2. Health equation

We now turn to the estimated effects of education and income on health, comparing estimates from the ordered probit and HOPIT models to gauge the degree of bias generated by reporting heterogeneity. Given that the scale of the latent variable is not identifiable in the ordered probit model, the constant term and the variance are

usually set equal to 0 and 1, respectively. Here, in order to make the estimated effects from the two models comparable, we fix the latent scale of the ordered probit model by setting the constant term and the variance equal to those estimated by the HOPIT model. The resulting coefficients of education and income in the health equations, (1) and (7), are shown in tables 7 and 8.

Tables 7&8

Let us start by analysing the income effects. For China and India the ordered probit results indicate significant positive relationships between income and SAH and each of the health domains, even without any adjustment for reporting heterogeneity. For Indonesia, the unadjusted income effects are positive but significant only for two of the six health domains.

For 12 of the 18 cases (6 health domains by 3 countries), the HOPIT adjustment increases the magnitude of the income effect. In the remaining 6 cases, the magnitude of the effect remains constant or is slightly reduced. In the case of Indonesia, the effect becomes significant for two more domains. These results confirm that the direction of the HOPIT adjustment is in line with the sign of the income coefficient in the last cut-point (tables 4 and 5 above), even when the cut-point shift is not uni-directional. The positive association between income and health is underestimated if reporting heterogeneity by income is not accounted for (for 12 of the 18 cases analysed here). This results especially from the fact that richer individuals have higher standards concerning the meaning of having no difficulties in a given health domain.

Table 8 presents the estimated effects of education on SAH, according to the ordered probit model, and health by domain, according to ordered probit and HOPIT models. For Indonesia and India, the education coefficients are significantly positive in all the ordered probit models, confirming a positive association between health and education, before the correction for reporting bias. The ordered probit models

estimated with the Chinese sample do not show evidence of a positive influence of education on health. The estimated effects are positive in only 3 health domains (*pain* and *self care*), albeit not significant. For 2 domains (*cognition* and *affect*) and for SAH, the estimated education effects are significantly negative. This may reflect the stage of development in China, not yet reached in India and Indonesia, where it is the better educated, more wealthy individuals that have the tastes and the incomes to engage in unhealthy lifestyles. Analysis of the Chinese Health and Nutrition Survey shows that higher educated groups are more likely to adopt unhealthy lifestyles, defined by obesity, lack of physical activity, smoking and drinking behaviour (Kim et al, 2004). However, the same analysis also finds that unhealthy lifestyles are more prevalent amongst those with high incomes, which is inconsistent with the gradient we find.

The vignette adjustment for reporting bias leads to a decrease of all but one (*pain*, China) of the education coefficients across domains and countries. More educated people tend to overreport their health (in particular, they are almost always more likely to report no difficulties in a given domain), which means that the estimated effects of education on health would be understated if this reporting bias was not accounted for. This result is perhaps surprising. It does not support the contention that education raises the expectations of individuals with respect to their health. Rather, it suggests that the better educated are more likely to tolerate ill-health.

6. CONCLUSION

In this paper we have investigated for the three low income Asian countries (India, Indonesia and China) whether health reporting tendencies affect the strength of the association between indicators of self-reported health on the one hand, and indicators of socio-economic status like income and education on the other hand. In order to do this, we have exploited the richness of the WHO-MCS data which have collected,

in addition to assessments of respondents' health domains, also their assessments for a large number of vignette descriptions of health domains. Our findings are as follows. First, we find that, even in the standard ordered probit models with uniform cut-points, household income has a positive and significant influence on many health domains. The same is true for schooling except in China, where it was found to have a (small but significant) negative effect on two health domains. Secondly, on the basis of our likelihood ratio tests, the hypothesis of homogeneous reporting of health domains is rejected for almost all our domains for our four determinants of cut-point shift: age, gender, income and schooling. This implies that failure to take this heterogeneity into account could lead to serious bias in the estimation of the true effects of these covariates on a person's own health. Thirdly, when we allow for heterogeneous cut-points using the hierarchical ordered probit model, we find that the income effect increases. The magnitude of the change varies from a 1% to a 300% increase. This is because higher income individuals appear to use higher standards for good health than lower income individuals. As a result, unadjusted estimates of income-related health inequality will tend to underestimate true inequality. Fourth, allowing for heterogeneity often has the opposite effect for schooling. For India and Indonesia, and for several domains, the effect of allowing for heterogeneity is to (slightly) reduce the coefficient of education. Apparently, lower educated use higher standards of good health.

REFERENCES

Baker J, van der Gaag J. Equity in health care and health care financing: Evidence from five developing countries. In: Van Doorslaer E, Wagstaff E, Rutten F, editors. Equity in the finance and delivery of health care: an international perspective. Oxford: Oxford University Press; 1993.

Contoyannis P, Jones AM, Rice. The dynamics of health in the British Household

Panel Survey, *Journal of Applied Econometrics*, 2004. 19: 473-503.

Eurostat. Self-reported health in the European Community. *Statistics in focus, population and social conditions*. ISSN 10244352. Eurostat, 1997.

Kim, S., M. Symons and B.M. Popkin. Contrasting socioeconomic profiles related to healthier lifestyles in China and the United States, *American Journal of Epidemiology*, 2004. 159 (2): 184-91.

King, G., C. Murray, J. Salomon, and A. Tandon. 2004. Enhancing the Validity and Crosscultural Comparability of Measurement in Survey Research, *American Political Science Review* 98(1), 567-583.

Lindeboom, M and E. van Doorslaer. Cut-point shift and index shift in self-reported health. *Journal of Health Economics*, Volume 23, Issue 6, November 2004, Pages 1083-1099.

Mathers CD, Douglas RM. Measuring progress in population health and well-being. In: Eckersley R, ed. *Measuring progress: is life getting better?* Collingwood, CSIRO Publishing, 1998:125-155.

Murray CJL. Epidemiology and morbidity transitions in India. In: Dasgupta M, Chen LC, Krishnan TN, eds. *Health, poverty and development in India*. Delhi, Oxford University Press, 1996:122-147.

Murray CJL, Chen LC. Understanding morbidity change. *Population and Development Review*, 1992, 18(3):481-503.

Murray, CJL, Tandon, A., Salomon, J.A., Mathers, C.D, Sadana, R. Cross-Population Comparability of Evidence for Health Policy. In: Murray CJL, Evans DB, eds. *Health systems performance assessment: debates, methods and empiricism*. Geneva, World Health Organization, 2003.

Tandon, A., C.J.L. Murray, J.A. Salomon, G. King. Statistical Models for Enhancing Cross-Population Comparability. In: Murray CJL, Evans DB, eds. *Health systems performance assessment: debates, methods and empiricism*. Geneva, World

Health Organization, 2003.

Üstün TB et al. WHO Multi-country Survey Study on Health and Responsiveness 2000-2001. In: Murray CJL, Evans DB, eds. Health systems performance assessment: debates, methods and empiricism. Geneva, World Health Organization, 2003.

van Doorslaer E.1; Gerdtham U.-G. Does inequality in self-assessed health predict inequality in survival by income? Evidence from Swedish data. *Social Science and Medicine*, Volume 57, Number 9, November 2003, pp. 1621-1629(9).

Wagstaff A. (2001), Poverty and health, CMH WP#1.

Wagstaff A (2002) Poverty and health sector inequalities. *Bulletin of the World Health Organization* 80, 97-105.

Wagstaff, A., P. Paci, and E. van Doorslaer, On the measurement of inequalities in health. *Social Science and Medicine*, 1991. 33: p. 545-557.

APPENDIX: VIGNETTE DESCRIPTIONS

Mobility

1 - [Paul] is an active athlete who runs long distance races of 20 kilometres twice a week and engages in soccer with no problems.

2 - [Mary] has no problems with moving around or using her hands, arms and legs. She jogs 4 kilometres twice a week without any problems.

3 - [Rob] is able to walk distances of up to 200 metres without any problems but feels breathless after walking one kilometre or climbing up more than one flight of stairs. He has no problems with day-to-day physical activities, such as carrying food from the market.

4 - [Margaret] feels chest pain and gets breathless after walking distances of up to 200 metres, but is able to do so without assistance. Bending and lifting objects such as groceries produces pain.

5 - [Louis] is able to move his arms and legs, but requires assistance in standing up from a chair or walking around the house. Any bending is painful and lifting is impossible.

6 - [David] is paralysed from the neck down. He is confined to bed and must be fed and bathed by somebody else.

Affect

1 - [Ken] remains happy and cheerful almost all the time. He is very enthusiastic and enjoys life.

2 - [Henriette] remains happy and cheerful most of the time, but once a week feels worried about things at work. She gets depressed once a month and loses interest but is able to come out of this mood within a few hours.

3 - [Jan] feels nervous and anxious. He is depressed nearly every day for 3-4 hours thinking negatively about the future, but feels better in the company of people or when doing something that really interests him.

4 - [Eva] feels worried all the time about things at work and home, and feels that they will go wrong. She gets depressed once a week for a day, thinking negatively about the future, but is able to come out of this mood within a few hours.

5 - [John] feels tense and on edge all the time. He is depressed nearly everyday and feels hopeless. He also has a low self esteem, is unable to enjoy life, and feels that he has become a burden.

6 - [Roberta] feels depressed all the time, weeps frequently and feels completely hopeless. She feels she has become a burden, feels it is better to be dead than alive, and often plans suicide. (q2307b)

Pain

1 - [Laura] has a headache once a month that is relieved one hour after taking a pill. During the headache she can carry on with her day to day affairs.

2 - [Phil] has pain in the hip that causes discomfort while going to sleep. The pain is there throughout the day but does not stop him from walking around.

3 - [Patricia] has a headache once a week that is relieved 3-4 hours after taking a pill. During the headache she has to lie down, and cannot do any other tasks.

4 - [Mark] has joint pains that are present almost all the time. They are at their worst in the first half of the day. Taking medication reduces the pain though it does not go away completely. The pain makes moving around, holding and lifting things, quite uncomfortable.

5 - [Jim] has back pain that makes changes in body position very uncomfortable. He is unable to stand or sit for more than half an hour. Medicines decrease the pain a little, but it is there all the time and interferes with his ability to carry out even day to day tasks.

6 - [Tom] has a toothache for about 10 minutes, several times a day. The pain is so intense that Tom finds it difficult to concentrate on work.

7 - [Steve] has excruciating pain in the neck radiating to the arms that is very minimally relieved by any medicines or other treatment. The pain is sharp at all times and often wakes him from sleep. It has necessitated complete confinement to the bed and often makes him think of ending his life.

Self care

1 [Helena] keeps herself neat and tidy. She requires no assistance with cleanliness, dressing and eating.

2 [Anne] takes twice as long as others to put on and take off clothes, but needs no help with this. She is able to bathe and groom herself, though that requires effort and leads to reducing the frequency of bathing to half as often as before. She has no problems with feeding.

3 [Paul] has no problems with cleanliness, dressing and eating. However, he has to wear clothes with special fasteners as joint problems prevent him from buttoning and

unbuttoning clothes.

4 [Peter] can wash his face and comb his hair, but cannot wash his whole body without help. He needs assistance with putting clothes on over his head, but can put garments on the lower half of his body. He has no problems with feeding.

5 [John] cannot wash, groom or dress himself without personal help. He has no problems with feeding.(q2301a)

6 [Rachel] feels pain and discomfort while washing, and in combing her hair. As a result, she neglects her personal appearance. She needs assistance with putting on and taking off clothes. She has no problems with feeding.

7 [Sue] requires the constant help of a person to wash and groom herself and has to be dressed and fed.

Cognition

1 - [Rob] can do complex mathematical problems in his mind. He can pay attention to the task at hand for long uninterrupted periods of time. He can remember names of people, addresses, phone numbers and such details that go back several years.

2 - [Sue] can only count money and bring back the correct change after shopping. Mental arithmetic is otherwise a problem. She can find her way around the neighbourhood and know where her own belongings are kept.

3 - [Henriette] can pay attention to the task at hand for periods of up to one hour, with occasional distractions and can quickly return to the task. She can remember names of people she meets often, their addresses and important numbers, but occasionally has to remind herself of the names of distant relatives or acquaintances.

4 - [Helena] can remember details of events that have taken place or names of people she has met many years ago, She can do everyday calculations in her mind. During periods of anxiety lasting a few hours, she becomes confused and cannot think very clearly.

5 - [Tom] finds it difficult to concentrate on reading newspaper articles, or watching

television programmes. He is forgetful and once a week or so, he misplaces important things, such as keys or money, and spends a considerable amount of time looking for them, but is able to find them eventually.

6 - [Julian] is easily distracted, and within 10 minutes of beginning a task, his attention shifts to something else happening around him. He can remember important facts when he tries, but several times a week finds that he has to struggle to recollect what people have said or events that have taken place recently.

7 - [Christian] is very forgetful and often loses his way around places which are not very familiar. He needs to be prompted about names of close relatives and loses important things such as keys and money, as he cannot recollect where they have been kept. He has to make notes to remind himself to do even very important tasks.

8 - [Peter] does not recognize even close relatives and cannot be trusted to leave the house unaccompanied for fear of getting lost. Even when prompted, he shows no recollection of events or recognition of relatives.

Usual

1 - [John] is a teacher and goes to work regularly. He teaches the senior grades and takes classes for 6 hours each day. He prepares lessons and corrects exam papers. Students come to him for advice.

2 - [Dan] is a mason in a building firm. Three to four times per week, he is noticed to leave his bricklaying tasks incomplete. With help and supervision, he is able to use his skills to finish the walls of the buildings well.

3 - [Mathew] is a clerk in the local government office. He maintains ledgers with no errors and keeps them up to date. However, he ends up not doing any work for a day once every 2 weeks or so because of a migraine headache.

4 - [Maria] is an accountant in the local bank. She is regularly at work. However, she makes minor errors in the accounts and tends to postpone tasks. She delays producing account statements and is late on deadlines.

5 - [Carol] is a housewife who leaves most chores around the house half done. Even with domestic help she cannot complete important tasks in time, such as getting her son ready for school. Her husband has had to take over the cooking.

6 - [Doris] is a housewife and does most of the cooking and cleaning around the house. About once a week she leaves tasks half done. Her cooking has deteriorated and the house is not as clean as it used to be. She also takes about twice as long to do the chores.

7 - [Karen] is a teacher and has had to miss work for 2 weeks in the past month. Even now she feels tired and exhausted, and cannot stand for long periods in the classroom. Colleagues notice that she is making serious mistakes in correcting answer papers.

8 - [Jack] is a clerk at the local post office. He just sits around all day and cannot engage in any work. He cannot sort letters, manage the counter or interact with customers. His employers are considering replacing him.

Table 1: Frequencies of general self-assessed health by country

	Indonesia	India	China
SAH			
Very bad	21	59	56
Bad	153	399	215
Moderate	1,515	1,254	1,799
Good	4,100	2,659	2,864
Very Good	926	758	2,041
N	6715	5129	6975

Table 2: Frequencies of own health and vignettes by domain and country

	Indonesia									India									China									
	own	vig1	vig2	vig3	vig4	vig5	vig6	vig7	vig8	own	vig1	vig2	vig3	vig4	vig5	vig6	vig7	vig8	own	vig1	vig2	vig3	vig4	vig5	vig6	vig7	vig8	
Mobility																												
Extreme	0.19	0.39	0.42	1.04	2.82	5.78	45.97			0.76	0.04	0.12	0.75	2.25	9.78	63.79			0.17	0.25	0.42	1.54	1.71	6.78	61.70			
Severe	0.92	4.09	3.05	10.35	36.36	50.44	40.12			5.58	0.91	1.62	8.48	30.38	54.08	29.28			0.80	1.20	1.21	4.77	24.73	44.34	26.63			
Moderate	2.16	5.63	6.44	26.60	34.82	24.67	6.05			7.35	0.43	2.01	26.04	41.17	25.03	3.90			3.51	2.21	4.96	20.89	47.63	34.14	5.61			
Mild	4.65	11.71	15.69	34.31	18.80	12.31	3.91			22.19	2.80	4.77	50.02	24.03	10.56	1.93			15.07	5.94	17.50	59.13	23.27	12.50	3.92			
None	92.08	78.18	74.41	27.70	7.21	6.79	3.94			64.13	95.82	91.49	14.71	2.17	0.55	1.10			80.45	90.39	75.91	13.68	2.66	2.24	2.13			
N	6715	3373	3372	3372	3372	3372	3372			5129	2538	2537	2535	2538	2537	2538			6975	3569	3566	3567	3567	3568	3567			
Affect																												
Extreme	0.24	0.90	1.02	1.73	1.32	14.23	38.08			1.15	0.24	0.16	0.95	1.98	31.94	39.02			0.24	1.59	0.22	0.33	0.66	32.69	50.30			
Severe	1.04	3.77	10.34	21.45	17.04	56.07	45.67			7.92	1.59	9.60	17.68	20.78	60.19	54.48			1.33	1.15	2.25	12.95	8.23	46.43	34.89			
Moderate	4.96	5.20	38.55	36.02	42.44	19.31	7.53			9.50	1.11	30.61	36.24	41.00	5.22	3.65			6.26	2.20	14.16	43.12	32.80	13.46	6.53			
Mild	11.85	13.51	41.72	32.50	32.99	7.59	3.77			22.62	5.23	54.56	42.90	34.66	2.65	1.35			33.21	8.84	69.92	38.45	53.32	5.22	4.00			
None	81.91	76.63	8.37	8.30	6.22	2.81	4.96			58.82	91.83	5.08	2.22	1.59		1.51			58.94	86.22	13.45	5.16	4.99	2.20	4.28			
N	6715	1673	1673	1674	1673	1673	1673			5129	1261	1261	1261	1261	1246	1261			6975	1822	1822	1823	1823	1820	1823			
Pain																												
Extreme	0.25	0.95	1.43	8.83	4.35	6.08	8.70	47.13		1.07	0.63	3.37	4.94	8.69	4.78	11.99	48.46			0.14	3.13	0.80	8.58	3.67	1.41	7.65	61.37	
Severe	2.19	6.62	20.98	44.45	44.64	49.76	52.56	39.23		8.21	11.05	33.91	53.13	68.62	59.33	58.70	47.83			1.48	16.67	6.43	35.25	36.86	19.23	33.80	27.69	
Moderate	10.93	26.34	44.46	30.19	31.23	29.14	26.82	7.12		13.10	25.78	38.29	30.09	16.74	27.35	18.34	2.60			7.53	39.15	35.64	41.45	45.25	42.01	40.54	6.98	
Mild	29.54	55.48	27.23	13.13	16.39	10.43	9.59	3.83		27.43	56.90	23.34	11.68	5.48	8.31	10.66	1.10			36.77	39.22	52.24	13.24	13.04	35.09	16.72	3.15	
None	57.09	10.61	5.90	3.40	3.40	4.59	2.32	2.69		50.19	5.64	1.10	0.16	0.47	0.24	0.31				54.09	1.84	4.90	1.47	1.16	2.27	1.29	0.80	
N	6715	1678	1678	1676	1678	1678	1678	1672		5129	1276	1277	1276	1278	1276	1276	1269			6975	1632	1633	1631	1633	1633	1633	1618	
Self																												
Extreme	0.18	0.30	1.55	2.74	3.22	6.32	4.17	26.04		0.66	0.24	1.72	3.13	2.04	15.32	7.13	37.12			0.10	0.43	0.37	1.22	1.41	6.98	2.70	45.19	
Severe	0.49	3.46	13.05	28.37	37.13	42.73	40.35	51.43		3.06	2.04	37.23	38.87	34.95	44.41	49.61	51.37			0.40	1.10	6.18	10.66	17.77	44.40	15.63	40.05	
Moderate	1.25	6.26	44.10	41.24	36.77	21.87	32.84	11.20		4.70	2.98	41.93	33.39	45.45	14.23	28.53	8.14			1.45	3.06	30.86	31.78	48.22	30.80	40.63	9.86	
Mild	3.56	17.82	31.17	22.35	15.61	15.44	15.55	7.15		16.79	3.13	17.48	23.51	15.75	9.54	13.32	3.13			6.48	11.21	53.03	49.66	30.88	14.21	35.85	4.04	
None	94.52	72.17	10.13	5.30	7.27	13.65	7.09	4.17		74.79	91.61	1.65	1.10	1.80	16.50	1.41	0.23			91.57	84.20	9.55	6.67	1.72	3.61	5.21	0.86	
N	6715	1678	1678	1678	1678	1678	1678	1678		5129	1276	1276	1276	1276	1279	1276	1277			6975	1633	1633	1633	1632	1633	1632	1633	
Cognition																												
Extreme	0.13	0.36	1.57	0.73	0.97	6.53	5.94	12.22	20.31	0.58	0.08	0.16	0.16	0.87	2.05	6.38	16.97	17.30	0.10	0.68	1.14	1.03	0.46	7.02	3.24	5.87	37.72	
Severe	1.07	3.99	14.69	9.02	18.56	47.61	38.91	50.70	56.77	4.04	1.97	5.29	20.08	17.92	35.20	48.56	58.72	66.03	1.19	0.57	13.91	4.64	3.70	32.53	20.70	35.97	41.03	
Moderate	4.90	6.53	27.39	33.90	33.74	31.70	37.70	25.47	14.57	8.34	3.08	21.33	34.39	29.76	37.96	26.16	19.57	11.14	5.42	2.28	30.67	17.01	20.68	36.99	41.51	39.05	14.07	
Mild	12.86	16.38	33.07	43.70	37.06	11.49	14.48	9.13	5.20	19.83	9.40	45.66	38.89	42.46	23.68	17.70	4.26	4.50	25.46	7.01	40.59	49.37	57.38	19.41	29.27	16.59	5.19	
None	81.03	72.73	23.28	12.65	9.67	2.66	2.97	2.48	3.14	67.21	85.47	27.57	6.48	9.00	1.10	1.20	0.47	1.03	67.83	89.46	13.68	27.95	17.78	4.05	5.28	2.51	1.99	
N	6715	1654	1654	1652	1654	1653	1650	1653	1654	5129	1266	1266	1265	1267	1267	1254	1267	1266	6975	1755	1754	1746	1755	1752	1667	1754	1755	
Usual																												
Extreme	0.31	0.54	1.70	3.93	4.53	5.51	3.99	5.26	16.88	1.42	0.32	1.43	3.63	3.47	4.74	3.32	4.35	22.02	0.47	0.80	0.90	2.39	0.34	6.10	2.34	4.73	39.98	
Severe	1.53	3.99	21.39	28.23	35.25	40.17	37.33	46.25	56.99	4.91	6.88	21.72	20.76	45.15	47.51	51.11	66.43	52.33	0.89	0.57	5.33	9.64	2.05	27.19	14.64	25.43	38.77	
Moderate	3.05	7.80	44.85	34.89	33.92	31.82	40.83	31.26	16.94	6.75	5.45	37.63	32.44	31.25	35.97	35.70	22.33	15.55	2.90	2.85	24.51	28.22	10.66	40.19	41.14	46.24	13.75	
Mild	7.94	17.71	24.79	27.63	20.92	16.52	14.82	11.06	6.17	21.19	6.25	25.46	41.52	18.55	9.88	8.93	6.41	8.52	15.48	12.71	50.39	49.54	48.06	20.41	36.24	19.95	5.50	
None	87.16	69.95	7.27	5.32	5.38	5.99	3.02	6.17	3.02	65.72	81.11	13.76	1.66	1.58	1.90	0.95	0.48	1.58	80.26	83.07	18.87	10.21	38.88	6.10	5.64	3.65	2.00	
N	6715	1654	1650	1654	1654	1653	1653	1654	1653	5129	1265	1257	1267	1267	1265	1266	1263	1267	6975	1754	1669	1754	1754	1754	1755	1754	1746	

Table 3: Descriptives statistics of covariates

Variables	Indonesia		India		China	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Female	0.528	0.499	0.534	0.499	0.457	0.498
Age3044	0.417	0.493	0.368	0.482	0.382	0.486
Age4559	0.183	0.387	0.222	0.416	0.265	0.442
Age60	0.097	0.296	0.151	0.358	0.107	0.309
Educ	7.825	4.450	3.769	4.987	9.069	4.194
Log(Inc)	12.107	1.271	6.242	1.161	5.393	1.418
N	6715		5129		6975	

Table 4: Estimated coefficients of LOG(INCOME) in the cut-points

	Indonesia				India				China			
	$\gamma^1_{\text{Log(INC)}}$	$\gamma^2_{\text{Log(INC)}}$	$\gamma^3_{\text{Log(INC)}}$	$\gamma^4_{\text{Log(INC)}}$	$\gamma^1_{\text{Log(INC)}}$	$\gamma^2_{\text{Log(INC)}}$	$\gamma^3_{\text{Log(INC)}}$	$\gamma^4_{\text{Log(INC)}}$	$\gamma^1_{\text{Log(INC)}}$	$\gamma^2_{\text{Log(INC)}}$	$\gamma^3_{\text{Log(INC)}}$	$\gamma^4_{\text{Log(INC)}}$
Mobility	0.028 (2.033)	-0.007 (-0.786)	-0.003 (-0.327)	0.002 (0.192)	0.000 (0.016)	-0.060 (-4.766)	-0.033 (-2.686)	0.016 (1.075)	0.011 (0.972)	0.001 (0.069)	0.005 (0.6)	-0.015 (-1.714)
Cognition	0.016 (0.943)	0.010 (1.032)	0.041 (4.349)	0.046 (4.364)	0.012 (0.523)	-0.015 (-1.048)	0.033 (2.334)	0.005 (0.258)	0.011 (0.716)	-0.003 (-0.246)	0.023 (2.448)	0.010 (0.851)
Pain	-0.028 (-2.268)	0.007 (0.696)	-0.001 (-0.095)	0.011 (0.76)	0.000 (-0.003)	-0.016 (-1.181)	0.005 (0.321)	0.056 (2.146)	0.020 (1.409)	0.033 (3.261)	0.028 (2.778)	0.056 (3.579)
Self care	-0.067 (-5.611)	-0.014 (-1.364)	0.008 (0.718)	-0.002 (-0.166)	0.016 (0.807)	0.014 (1.065)	0.044 (3.208)	0.053 (2.931)	0.050 (2.994)	0.072 (6.133)	0.067 (6.351)	0.037 (2.753)
Usual activities	-0.029 (-2.316)	0.007 (0.772)	0.029 (3.158)	0.043 (3.924)	0.036 (1.729)	0.003 (0.231)	0.055 (3.939)	0.044 (2.365)	-0.025 (-1.609)	-0.027 (-2.528)	0.008 (0.856)	-0.012 (-1.078)
Affect	-0.016 (-1.071)	-0.019 (-1.748)	0.013 (1.202)	0.037 (3.065)	0.026 (1.208)	-0.027 (-1.619)	0.025 (1.547)	-0.002 (-0.092)	0.009 (0.693)	0.019 (1.691)	0.027 (2.821)	0.033 (2.996)

Note: t-statistics in parentheses

Table 5: Estimated coefficients of EDUC in the cut-points

	Indonesia				India				China			
	$\gamma^1_{\text{Log(EDUC)}}$	$\gamma^2_{\text{Log(EDUC)}}$	$\gamma^3_{\text{Log(EDUC)}}$	$\gamma^4_{\text{Log(EDUC)}}$	$\gamma^1_{\text{Log(EDUC)}}$	$\gamma^2_{\text{Log(EDUC)}}$	$\gamma^3_{\text{Log(EDUC)}}$	$\gamma^4_{\text{Log(EDUC)}}$	$\gamma^1_{\text{Log(EDUC)}}$	$\gamma^2_{\text{Log(EDUC)}}$	$\gamma^3_{\text{Log(EDUC)}}$	$\gamma^4_{\text{Log(EDUC)}}$
Mobility	0.009 (2.285)	0.003 (1.159)	-0.003 (-1.058)	-0.017 (-6.308)	-0.001 (-0.269)	0.002 (0.696)	-0.001 (-0.179)	-0.008 (-2.148)	-0.007 (-1.684)	-0.007 (-2.172)	-0.007 (-2.148)	-0.002 (-0.695)
Cognition	0.004 (0.883)	0.003 (0.906)	-0.014 (-4.621)	-0.020 (-5.655)	0.000 (-0.02)	0.000 (0.06)	-0.003 (-0.759)	-0.007 (-1.644)	-0.010 (-1.858)	-0.021 (-5.834)	-0.017 (-5.118)	-0.007 (-1.806)
Pain	0.003 (0.615)	0.003 (0.874)	-0.003 (-1)	-0.015 (-3.574)	0.009 (2.062)	-0.003 (-0.868)	-0.013 (-3.436)	-0.011 (-1.524)	-0.002 (-0.406)	-0.015 (-4.133)	-0.010 (-2.784)	0.013 (2.125)
Self care	0.018 (3.592)	0.007 (2.457)	-0.001 (-0.219)	-0.018 (-4.957)	-0.005 (-1.153)	-0.006 (-1.765)	-0.003 (-0.898)	-0.008 (-1.633)	-0.019 (-3.165)	-0.013 (-3.074)	-0.004 (-1.122)	-0.001 (-0.201)
Usual activities	0.002 (0.461)	0.005 (1.654)	-0.005 (-1.645)	-0.021 (-5.377)	-0.001 (-0.106)	-0.006 (-1.999)	-0.009 (-2.57)	-0.012 (-2.688)	-0.011 (-2.024)	-0.015 (-3.995)	-0.014 (-4.255)	-0.001 (-0.278)
Affect	0.002 (0.391)	0.000 (-0.069)	-0.004 (-1.112)	-0.015 (-3.811)	-0.001 (-0.251)	-0.010 (-2.289)	-0.011 (-2.608)	-0.009 (-1.562)	0.005 (1.086)	0.001 (0.257)	-0.005 (-1.368)	-0.004 (-0.989)

Note: t-statistics in parentheses

Table 6: Likelihood ratio tests of equality of cut-points by covariates (p-values)

	Indonesia					India					China				
	All	Female	Age	Educ	Log(Inc)	All	Female	Age	Educ	Log(Inc)	All	Female	Age	Educ	Log(Inc)
Mobility	0.000	0.214	0.001	0.000	0.186	0.000	0.000	0.045	0.184	0.000	0.000	0.000	0.000	0.103	0.214
Cognition	0.000	0.410	0.099	0.000	0.000	0.000	0.000	0.045	0.184	0.000	0.000	0.538	0.036	0.000	0.059
Pain	0.000	0.015	0.000	0.002	0.087	0.000	0.000	0.289	0.001	0.113	0.000	0.000	0.000	0.000	0.001
Self care	0.000	0.198	0.001	0.000	0.000	0.000	0.000	0.004	0.244	0.010	0.000	0.882	0.000	0.005	0.000
Usual activities	0.000	0.020	0.335	0.000	0.000	0.000	0.000	0.001	0.036	0.000	0.000	0.213	0.102	0.000	0.009
Affect	0.001	0.116	0.195	0.003	0.002	0.000	0.000	0.775	0.073	0.010	0.124	0.946	0.162	0.369	0.017

Table 7: Estimated coefficients of LOG(INCOME) before and after adjustment - $\beta_{\text{Log(INC)}}$

	Indonesia		India		China	
	Before	After	Before	After	Before	After
SAH	0.020 (1.78)	- -	0.066 (4.715)	- -	0.067 (6.802)	- -
Mobility	0.053 (2.069)	0.054 (2.007)	0.070 (2.826)	0.068 (2.504)	0.109 (6.585)	0.099 (5.38)
Cognition	0.019 (1.036)	0.064 (3.067)	0.117 (4.391)	0.125 (4.145)	0.076 (5.921)	0.088 (5.459)
Pain	0.013 (0.991)	0.021 (1.156)	0.063 (2.329)	0.092 (2.861)	0.078 (5.705)	0.125 (6.783)
Self care	0.056 (1.622)	0.052 (1.412)	0.084 (3.43)	0.134 (4.623)	0.151 (4.936)	0.192 (5.774)
Usual activities	0.060 (2.397)	0.100 (3.677)	0.131 (5.062)	0.176 (5.91)	0.105 (5.533)	0.097 (4.535)
Affect	0.016 (0.776)	0.047 (1.999)	0.177 (5.623)	0.176 (4.912)	0.095 (7.367)	0.126 (7.953)

Note: t-statistics in parentheses

Table 8: Estimated coefficients of EDUCATION before and after adjustment - β_{EDUC}

	Indonesia		India		China	
	Before	After	Before	After	Before	After
SAH	0.019 (5.655)	- -	0.039 (10.796)	- -	-0.012 (-3.357)	- -
Mobility	0.047 (5.296)	0.033 (3.504)	0.048 (7.183)	0.041 (5.6)	-0.005 (-0.88)	-0.008 (-1.246)
Cognition	0.046 (8.179)	0.028 (4.28)	0.065 (8.963)	0.059 (7.287)	-0.015 (-3.129)	-0.024 (-4.185)
Pain	0.022 (5.423)	0.011 (2.036)	0.069 (9.701)	0.059 (6.788)	0.000 (0.043)	0.007 (0.953)
Self care	0.064 (5.383)	0.048 (3.774)	0.057 (8.275)	0.049 (5.96)	0.013 (1.143)	0.011 (0.922)
Usual activities	0.061 (7.253)	0.043 (4.742)	0.070 (9.717)	0.058 (7.016)	0.000 (0.046)	-0.003 (-0.399)
Affect	0.026 (4.092)	0.013 (1.8)	0.061 (7.403)	0.052 (5.459)	-0.015 (-3.137)	-0.019 (-3.189)

Note: t-statistics in parentheses