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Who Benefits from Government Health Spending and Why?

A Global Assessment

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Abstract

This paper uses a common household survey instrument and a common set of imputation assumptions to estimate the pro-poorness of government health expenditure (GHE) across 69 countries at all levels of income. Among the 66 countries for which the incidence of total GHE can be estimated, the mean and median concentration index values imply GHE is, on average, pro-rich. In only 26 countries, however, is the index statistically significant at the five percent level; in all but six of these, GHE is pro-rich. Government health expenditure on contracted private facilities emerges as significantly pro-rich for all types of care, and in almost all Asian countries government health expenditure overall is significantly pro-rich. The pro-poorness of government health expenditure at the country level is significantly and positively correlated with gross domestic product per capita and government health expenditure per capita, significantly and negatively correlated with the share of government facility revenues coming from user fees, and significantly and positively correlated with six measures of the quality of a country's governance; it is not, however, correlated with the size of the private sector nor with the degree to which the private sector delivers care disproportionately to the better-off. Because poorly-governed countries are underrepresented in the sample, government health expenditure is likely to be even more pro-rich in the world as a whole than it is in the countries in this study.

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Who Benefits from Government Health Spending and Why? A Global Assessment

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1. Introduction

A commonly stated reason why governments spend on the health sector, and why donors supplement such spending in developing countries, is to reduce inequalities in the distributions of health care utilization and health status compared to what they would have been otherwise. Income redistribution may be a second – although typically not explicit – objective: if there is limited scope to levy income taxes, as is the case in many developing countries, a government may seek to redistribute income by financing health care at a quality level that is just low enough for the better off to decide to seek their health care privately (Besley and Coate 1991). Yet despite the broad consensus that government health spending (GHE) ought to disproportionately favor the poor, studies to date show that often the reality is exactly the opposite.[1]

This literature is not, however, without its limitations. First, most studies cover just one country or a few countries in a specific region; it is unclear therefore how representative the results are of the world as a whole.[2] Second, previous studies have either worked with secondary tabulated survey data or (probably better) have tried to harmonize ex post but often highly heterogeneous household survey data; as a result it is unclear how comparable the results are across

[1] BIA studies covering several countries include Castro-Leal et al. (1999; 2000), Filmer (2003), O'Donnell et al. (2007), Davoodi (2010). Mahal et al. (2001) report comparisons across India's states.

[2] There is only one previous multi-country benefit incidence analysis (BIA) study that has covered all regions of the world (Davoodi et al. 2010), which covers 56 countries. Others have focused on one region only: Castro-Leal et al. (1999; 2000) report results for a subset of African countries, while O'Donnell et al. (2007) report results for a subset of Asian economies.

countries.[3] Third, there has been variation between and within studies in the methods to impute subsidies at the individual level, even though it is known that different methods are likely to produce different results; this makes it even less clear how comparable the results are across studies and across countries within a cross-country comparative study.[4] Fourth, studies to date have paid scant attention to the issue of sampling variability; few have presented confidence intervals around their estimates of their indices of the pro-poorness of GHE.[5] Fifth, few comparative BIA studies go on to explore the issue of *why* countries vary in the degree to which GHE is pro-poor; those that do explore a narrow subset of possible influences, and none offers a coherent logical framework of the interrelationships between them.

In this paper we try to push the literature forward on all five fronts. First, we present results for as many as 69 countries across all regions of the world.[6] We compare our 69 countries with the remaining countries of the world on variables we find to be correlated with the pro-poorness of GHE in the WHS countries; based on these differences and correlations, we extrapolate the incidence of GHE in the countries we do not analyze. Second, our country estimates are based on microdata drawn from a single household survey instrument that was implemented in the 69 countries; our country estimates are, therefore, we believe, highly comparable.

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[3] Davoodi et al. (2010) and Filmer (2003) work with tabulated data. Studies that try to harmonize ex post household survey data include O'Donnell et al. (2007) and Castro-Leal et al. (1999; 2000).

[4] For example, O'Donnell et al. (2007) use the constant unit cost (CUC) assumption except in the case of India where they use the constant unit subsidy (CUS) assumption – these assumptions are explained below.

[5] Only one other study to date (O'Donnell et al. 2007) has computed standard errors for estimates of GHE incidence.

[6] The precise number of countries varies according to the analysis we do. We estimate the pro-poorness of overall GHE for 66 countries.

Third, we undertake cross-country comparisons only for countries for which we can compute benefit incidence using the same method. This consistency is important since it is known that the methods used to impute GHE at the individual level can dramatically affect the conclusion of a BIA study, including the answer to the fundamental question of whether spending disproportionately benefits the poor or better off (Wagstaff 2012). We also explore how our results vary according to which of three methods is used to impute subsidies at the individual level, and present some new insights into the data requirements of each of the three methods. Fourth, when comparing the incidence of GHE (using the concentration index) across countries, including at the subsector level, we also report 95 percent confidence intervals for the concentration index, which we obtain using bootstrapping. This allows us to be sure that when a country appears to have a pro-poor or pro-rich GHE distribution it is not due to sampling variability. Finally, we not only explore more possible reasons why countries vary in the degree to which their GHE is pro-poor, but we also suggest how they might fit together in a coherent logical framework. Our evidence takes the form of cross-country correlations backed up where possible by evidence on causality from the relevant literature.

The rest of the paper is organized as follows. Section 2 outlines the methods we use both to measure the incidence of GHE at the country level and to understand the sources of cross-country variation in the incidence of GHE. Section 3 outlines our data and discusses computation issues, again for both goals of the paper. Section 4 presents our results, starting with the evidence on GHE incidence at the country level and then moving to our results on the sources of cross-country variation. Section 5 contains a discussion and section 6 our conclusions.

2. Methods

2.1 Measuring inequality in subsidy incidence

Suppose for the moment we can observe subsidies at the individual level. Then we could measure the degree of inequality (by income or consumption) in subsidies for subsector k, S_k, by computing the concentration index (CI) (Kakwani et al. 1997). The CI for subsidies for subsector k, CI_{S_k}, is derived from a Lorenz-type plot of the cumulative share of the population ranked in ascending order of income (or consumption) on the x-axis and the cumulative share of subsidies on the y-axis. A negative (positive) value of the CI indicates a pro-poor (pro-rich) distribution (CI_{S_k} is bounded by -1 and +1). Of course, the amount of subsidy individual i gets from subsector k, S_{ki}, is not observed in a household survey, and has to be imputed.

2.2 Computing the incidence of subsidies at the subsector level

At the individual level, subsidies received by individual i from subsector k are equal to the difference between the costs incurred by the subsidy-receiving providers used by individual i and the fees paid by individual i to these providers:

$$(1) \qquad S_{ki} = C_{ki} - F_{ki} = c_{ki}q_{ki} - f_{ki}q_{ki} = q_{ki}(c_{ki} - f_{ki}) = q_{ki}s_{ki} \ .$$

Here, C_{ki}, are the costs incurred by providers in subsector k in providing services to individual i, F_{ki} are the fees paid by individual i to providers in subsector k, q_{ki} is the number of units of service of type k consumed by individual i, and c_{ki}, f_{ki} and s_{ki} are the unit costs, fees and subsidies respectively for sector k for individual i. We are likely to observe q_{ki} and f_{ki} in a household survey although in some surveys we do not observe both. By contrast, we do not observe c_{ki} in a household survey, and that is why imputation becomes necessary.

Three approaches to imputing subsidies at the individual level have been proposed (Wagstaff 2012). The first is the "constant unit cost" (CUC) approach which assumes that unit costs, c_{ki}, are constant across individuals and equal to c_k. In this case eqn (1) becomes

(2) $$S_{ki}^{CUC} = c_k q_{ki} - f_{ki} q_{ki}.$$

If data on the unit costs, c_k, are available from administrative data or a health facility survey, or have been estimated, and if individual-level data on the q_{ki} and f_{ki} are also available in the household survey, S_{ki}^{CUC} can be computed at the individual level, and the corresponding concentration index $CI_{S_k}^{CUC}$ can be calculated. Alternatively, as shown by Wagstaff (2012), $CI_{S_k}^{CUC}$ can be computed as:

(3) $$CI_{S_k}^{CUC} = \frac{C_k}{S_k} CI_{q_k} - \frac{F_k}{S_k} CI_{F_k},$$

where CI_{q_k} is the concentration index for utilization, CI_{F_k} is the concentration index for fees, F_{ki}, and C_k, S_k and F_k are aggregate costs, subsidies and fees respectively. The shortcut in eqn (3) is useful when the country has a set of national health accounts (NHA) that includes these aggregates: in this case, there is no need to get the unit cost data for each of the subsectors.

A problem with the CUC assumption is that it is hard to rationalize why people pay different amounts out-of-pocket for an outpatient visit or an inpatient admission; the assumption implies that people paying more out-of-pocket get a *smaller* subsidy.[7] In reality it seems likely that higher fees reflect at least more costly (and perhaps better quality) care, and that higher fees are not automatically associated with a smaller subsidy. A second approach (the "constant unit subsidy" or CUS assumption) which – unlike the CUC assumption – is consistent with this idea assumes that the unit subsidy, s_{ki}, is constant across for a given subsector k. In effect the government pays up to certain amount of the cost of care, and the user pays each additional dollar of cost themselves out-of-pocket. Eqn (1) in this case becomes (cf. Wagstaff 2012):

(4) $$S_{ki}^{CUS} = q_{ki}s_k \ ,$$

so that subsidies for subsector k are proportional to utilization for subsector k. Thus in this case, CI_{S_k} is simply equal to the CI for utilization (cf. Wagstaff 2012):

(5) $$CI_{S_k}^{CUS} = CI_{q_k}.$$

Note that to compute $CI_{S_k}^{CUS}$ we do not need to know the unit subsidy for subsector k, s_k. Nor do we need to know the c_{ki} and f_{ki}. Thus, not only is the assumption CUS

[7] The CUC assumption is more plausible if there are means-tested subsidies that are effectively targeted.

arguably more plausible than the CUC assumption, it is also less demanding in terms of data requirements.

A third approach (the "fees proportional to costs" assumption or FPC) is to assume that unit costs and fees are *proportional* to one another.[8] In this case, the user pays a constant fraction of the cost of care, and the subsidy they receive is proportional to the fees they pay. Under this assumption, the concentration index for subsidies is therefore equal to the CI concentration index for fees (cf. Wagstaff 2012):

(6) $CI_{S_k}^{FPC} = CI_{F_k}$.

Note that to compute $CI_{S_k}^{FPC}$ all we need are the individual-level data on fees, f_{ki}, and the variable used to rank individuals by their living standards.

The three approaches will give a different estimate of the extent to which subsidies are pro-poor or pro-rich. In the plausible case where fees are more pro-rich than utilization, Wagstaff (2012) has shown that the CUC assumption will lead to the least pro-rich distribution of subsidies and the FPC assumption the most pro-rich distribution; the CUS assumption falls somewhere in the middle. It is perfectly possible that subsidies emerge as pro-poor under the CUC assumption but pro-rich under the CUS and FPC assumptions.

[8] The assumption of proportionality may be too strong; a weaker version proposed by Wagstaff (2012) – which we do not explore in this paper – is to assume that unit costs are a linear function of fees.

2.3 Computing the incidence of subsidies at the sector level

Whichever method is used to impute subsector-specific subsidies, we can compute inequality in subsidies to the entire health sector as the concentration index for total subsidies, CI_S, which is equal to a weighted average of the concentration indices for the various subsectors where the weight for subsector k is equal to the subsector's share in total subsidies. Thus, we have:

$$(7) \qquad CI_S = \sum_k (S_k/S) CI_{S_k},$$

where S is the amount of subsidy going to the entire health sector. In many countries, a NHA is available containing data on S and with enough data to allow the S_k to be estimated.[9] When a NHA is not available, or when it does not include sufficiently detailed information to allow the S_k to be estimated, the values of S_k and their sum S can be estimated using microdata. We have:

$$(8) \qquad S_k = \sum_i c_{ki} q_{ki} - \sum_i f_{ki} q_{ki}$$
$$= \sum_i q_{ki} \frac{\sum_i c_{ki} q_{ki}}{\sum_i q_{ki}} - \sum_i q_{ki} \frac{\sum_i f_{ki} q_{ki}}{\sum_i q_{ki}} = Q_k \bar{c}_k - Q_k \bar{f}_k = Q_k (\bar{c}_k - \bar{f}_k),$$

where Q_k is the total number of units of service of type k across the entire population (e.g. the aggregate number of inpatient admissions), $\bar{c}_k$ is the average cost in the kth subsector per unit of utilization (e.g. per outpatient visit or per inpatient admission), and $\bar{f}_k$ is the average amount of fees paid in the kth subsector per unit of utilization. We can compute Q_k as:

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[9] Computing $CI_{S_k}^{CUC}$ using eqn (3) requires such data to be available.

(9) $Q_k = N \cdot \bar{q}_k$,

where N is the number of persons in the population, and $\bar{q}_k$ is the utilization rate for subsector k (e.g. the number of inpatient admissions per capita); often it will be possible to estimate the utilization rate from the household survey. Since what we need for eqn (7) are the subsidy shares, the population size, N, cancels out, and we have:

(10) $$\frac{S_k}{S} = \frac{Q_k(\bar{c}_k - \bar{f}_k)}{Q_1(\bar{c}_1 - \bar{f}_1) + Q_1(\bar{c}_2 - \bar{f}_2) + \cdots + Q_K(\bar{c}_K - \bar{f}_K)} = \frac{\bar{q}_k(\bar{c}_k - \bar{f}_k)}{\bar{q}_1(\bar{c}_1 - \bar{f}_1) + \bar{q}_2(\bar{c}_2 - \bar{f}_2) + \cdots + \bar{q}_K(\bar{c}_K - \bar{f}_K)}.$$

Data on the average costs, $\bar{c}_k$, would need to come from administrative data or from a health facility survey, while data on the average fees, $\bar{f}_k$, can be estimated from the household survey.

2.4 Understanding the sources of cross-country variation in subsidy incidence

Once we have estimates of the pro-poorness of GHE at the country level, we want to ask why some countries have more pro-poor distributions of GHE than others.

O'Donnell et al. (2007) suggest several factors that may account for the variation across countries in the pro-poorness of GHE. Richer countries, they argue, are more likely to have pro-poor distributions of GHE since they will have the resources to have a well-funded publicly-financed universal health system.[10] O'Donnell et al. also suggest that countries with higher levels of GHE will have more pro-poor (or less pro-rich) distributions of GHE. One explanation is that higher levels of GHE "afford… a wider geographic distribution of public health facilities and so bring services closer to poor, rural populations." Another is that the better off capture the initial dollars of GHE, but as spending increases and the needs of the better off decline, spending becomes more pro-poor. Finally, O'Donnell et al. suggest that the pro-poorness of GHE will be higher the bigger the quality gap between government services and private-sector alternatives, since the larger this gap the more likely it is that the better off will opt out of the public system; however, they do not test this hypothesis due to lack of data on quality.

The 2004 World Development Report (WDR) (World Bank 2003) sheds additional light on both the proximate and underlying causes of a pro-rich distribution of GHE. Governments often emphasize in their resource-allocation decisions facilities that cater disproportionally to the better off – an urban provincial hospital, for example. But even when governments allocate resources to providers catering to the poor, the resources often fail to reach the providers; funds leak as they are transferred from the center to the periphery, and being on the periphery the facilities catering to the poor suffer disproportionately from this leakage (Devarajan and Reinikka 2004; Lindelow 2008). Even when funds reach the

[10] O'Donnell et al. note that that a universal system can coexist with a private system that allows the better off "to bypass the bottlenecks and inconveniences of the public system." It is not obvious though that the degree of opting out need vary with the per capita income of a country.

periphery there is no guarantee that they will translate into services: doctors may not want to take a post in the periphery and when they do accept one they often fail to show up to work (Chaudhury et al. 2006); and drugs and other supplies are pilfered, often by frontline providers who 'borrow' them for their private practice (McPake et al. 1999). On the demand-side, partly because of the price and other financial costs associated with using services, and partly because they know that the facilities serving them are disproportionately unlikely to deliver needed services, the poor are less likely to seek care when they need it.

These are, of course, *proximate* causes of GHE failing to disproportionately benefit the poor. The WDR suggests that the *underlying* cause is a breakdown in accountability. Patients cannot hold publicly-financed providers directly accountable through the market mechanism; instead they rely on an indirect accountability mechanism, by holding policy makers accountable through the ballot box or other political process, and then having policy makers hold providers accountable for their performance (or not) through payment mechanisms, audits, etc. At both stages in this 'long route' of accountability, the poor are disadvantaged. Weaknesses in the electoral system result in their voices being heard less loudly, so policy makers worry more about being responsive to more affluent sections of the population. And even well-intentioned policy makers may find it harder to supervise and hold accountable providers in the periphery because of distance and topography, and because providers serving in such areas may have been more reluctant to work there than those working in the city, and are hence less committed.

The implication of the WDR's argument is that the international variation in the pro-poorness of GHE may reflect more than variation in the variables mentioned by O'Donnell et al. (2007). It may reflect variation in how well a country is governed; the extent to which publicly-financed facilities levy user fees; and the share of GHE absorbed by the hospital sector. Of course, both user fees and the share of GHE going to the hospital sector are really proximate causes, with the ultimate cause being weak accountability relations.

To test the above hypotheses, we present bivariate correlations (with bootstrapped standard errors) of the overall GHE CI with aggregate variables that capture the hypothesized influences, along with whatever evidence from the literature we can find that suggests that the correlations reflect causal effects. We do not present a multiple cross-country regression as O'Donnell et al. (2007) do. One reason is that such a regression risks giving the impression of having identified causal effects rather than just partial correlations. The other is that the partial correlations that the regression captures may obscure some of the important ways in which the hypothesized influences relate to one another. In section 5 we offer such an interpretation.

3. Data and computation

In this section, we detail the data that we have used and address some computational issues.

3.1 Data requirements for different approaches

Table 1 summarizes the three imputation methods and their data requirements, and how the calculation of the incidence of aggregate subsidies depends on whether NHA data or microdata on utilization and average fees are used. All three methods – CUC, CUS and FPC – require individual-level data containing a measure of the individual's living standards. The three approaches differ in terms of what additional data are required. All that is needed additionally under the FPC assumption are individual-level data on fees, f_{ki}. Under the CUS method, all that is needed additionally are individual-level data on the number of units of utilization, q_{ki}. Under the CUC method, there are two options. One (shown in the third row of the CUC column in Table 1) involves computing subsidies at the individual level using eqn (2): this requires individual-level data on q_{ki} and f_{ki}, as well as data on unit costs, c_k; the latter come from a health facility survey or administrative sources. The other option (shown in the first row of the CUC column in Table 1) involves using eqn (3): this requires individual-level data on q_{ki} and f_{ki} from the household survey, but rather than data on unit costs instead uses aggregate data on costs, subsidies and fees, which come from the NHA. To compute the incidence of subsidies at the sector level, we require data on the subsidy shares of each subsector: these can be estimated from the NHA (the second row of Table 1), or can be computed via eqn (10) using data on utilization rates (often using a household survey) and average fees (again typically from a household survey) and unit costs (from administrative data or health facility surveys) (shown in the bottom row of Table 1).

3.2 Household survey data

Our household survey data are from the World Health Survey (WHS). The WHS was fielded in the early 2000s in 70 countries.[11] The WHS asks about a broader range of issues than other standardized health surveys, such as the Demographic and Health Survey (DHS) and the Multiple Indicator Cluster Survey (MICS): it asks about use of inpatient and outpatient care, fees paid by the user, as well as the household's living standards. Furthermore, it is more representative of the world, covering lower-, middle- and high-income countries; we return to the issue of the WHS's representativeness below. Table A1 in the Appendix lists the WHS countries, the sample size, and indicates whether the survey collected data on utilization and on fees.

Households in the WHS are asked four questions covering their expenditure in the previous four weeks on: (i) food, (ii) housing-related costs, (iii) education, and (iv) other goods and services. This is far from the ideal measurement of household living standards. A typical survey living standards survey, such as the World

[11] One country (Turkey) had no utilization data. The total number of WHS countries for our purposes is therefore 69.

Bank's Living Standards Measurement Study, collects much more detailed expenditure information and also captures consumption rather than just expenditure (for example, home-grown food and the use value of family-owned housing). Even in comparison with household surveys with slimmer consumption or expenditure modules, the WHS's expenditure module is very brief. The consensus seems to be that (nonmedical) consumption may be underestimated in the WHS relative to other surveys (cf. Lu et al. 2009; Heijink et al. 2011; Raban et al. 2013).

The WHS asks a randomly-selected adult in the household about their use of inpatient care and outpatient care. We have focused on a 12-month window for both types of care. In both cases the respondent is asked whether the facility where care was most recently received was public or private.[12] In all but seven countries the WHS also records the name of the facility where outpatient care was received, enabling us to classify the facility as a hospital or a clinic.[13,14] Using the household expenditure variable and the utilization variable, we can get estimates of the CI_{q_k}

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[12] In Israel, many facilities were classified as NGO; we reclassified them as public on the grounds that NGO health plans in Israel receive an annual capitation fee per member from the Government and operate their own facilities (see p20 of the 2009 HiT). In Latin America, we re-classified social security facilities as public.

[13] We classified facilities as a clinic if did not have "hospital" in their name. In most countries, the name of the facility was in the local language, and we used Google Translate to find synonyms for hospital in the local language. We also searched through the names recorded in the WHS for abbreviations and for some countries asked local experts to identify hospitals by name (e.g. Ghana).

[14] In the seven countries where the WHS did not record the name of the facility where outpatient care was received (Australia, Brazil, Ethiopia, Hungary, Israel, the Netherlands, and Nepal), or the information recorded was unusable, we drew on institutional information contained in the NHA and in reports like WHO's Health in Transition (HiT) series, and adopted the following rules: (a) when the NHA or HiT indicates that only one type of government facility (e.g. hospital) provides outpatient care, we assigned all government outpatient care to that type of facility (Australia and the Netherlands are examples); (b) when the NHA or HiT indicates that only one type of private facility (e.g. clinic) provides outpatient care, we assign all private outpatient care to that type of facility (Australia and the Netherlands are again examples, as is Ethiopia); (c) when the NHA or HiT indicates that both types of government facility provide outpatient care, we assume that the concentration index is the same for both types of government facility (Ethiopia and Israel are examples); (d) when the NHA or HiT indicates that both types of private facility provide outpatient care, we assume that the concentration index is the same for both types of private facility (Israel is an example).

for 69 countries for the following six subsectors: (i) inpatient care in government hospitals; (ii) inpatient care in private hospitals; (iii) outpatient care in government hospitals; (iv) outpatient care in private hospitals; (v) outpatient care in government clinics (and other primary care providers); and (vi) outpatient care in private clinics. Three limitations of the WHS utilization data need flagging. First, we can tell only whether inpatient or outpatient care was received, not the number of contacts. Second, the information on whether a facility used was public or private, and the name of the facility, is only for the last facility visited. Third, in most countries, the WHS asks about outpatient care use only among people who had not received inpatient care. Since some countries did not follow the latter practice, we are able to get a sense – in these countries at least – of the likely bias this practice induces.

In 55 countries (the OECD countries are the 'missing' countries), the WHS also asks the same randomly selected household member about fees paid to the last-visited provider, f_{ki}. Using the fees variable and the ranking variable, we can estimate the CI_{F_k} for the non-OECD countries.

The WHS is also our main source of data on the utilization rate $\bar{q}_k$. The fact that the WHS captures only *whether* utilization has occurred in the recall period is not so much of a worry in the case of inpatient admissions given that so few people have more than one admission in any year. Since our data on unit costs ($\bar{c}_k$ in eqn (10)) are per inpatient *day* rather than per inpatient *admission*, we needed our utilization rate $\bar{q}_k$ to be the mean inpatient days per annum rather than the mean inpatient admission rate per annum. Fortunately, the WHS records the length of stay during the last admission, and not just whether the respondent was admitted to hospital.[15] In the case of outpatient visits, it *does* matter that the WHS records only whether utilization occurred and not the count of visits. Here we obtained data from international statistical sources[16] on the overall outpatient visit rate for as many countries as we could; we then applied the country-specific breakdown in the WHS data on where the last visit took place (i.e. public clinic, private clinic, public hospital, and private hospital) to get an estimate of the subsector-specific outpatient visit rates for each of the four subsectors. For the 38 countries where we could not get data on the overall outpatient visit rate, we imputed the rate from a regression that we estimated for the 32 countries for which we could find data; in this regression we included as predictors doctors per 1,000 persons, road density (km of road per 100 square km of land area), and gross national income per capita.[17]

3.3 Unit cost data

Our unit cost data ($\bar{c}_k$ in eqn (10)) are from the World Health Organization's "Choosing Interventions that are Cost Effective" (WHO-CHOICE) project.[18] WHO has estimated unit costs in most countries in the world for outpatient visits and

[15] The length of stay variable in the WHS is in categories, the top category being 15+ days. We assigned a value of 42.5 days to this last category. We obtained this number by adjusting the number of days in the top category until the mean across all countries in the WHS data was equal to the global mean length of stay for secondary-level hospitals in the WHO-CHOICE tool.
[16] The data sources included the WHO Europe Health for All Database (http://data.euro.who.int/hfadb), the PAHO Core Health Indicators Database (http://ais.paho.org/phip/viz/indicatorprofilebydomain.asp), and OECD Health Statistics (http://stats.oecd.org/index.aspx?DataSetCode=HEALTH_STAT#).
[17] The regression's adjusted R-squared is 0.29 and residual plots do not exhibit any pattern. The data on the three predictors came from the World Development Indicators. We assumed the reported number of doctor visits per inhabitant referred to the public sector only (the data usually come from health ministries who typically do not have data on private sector visits) and we then inflated these using the WHS private-public mix to get an estimate of the total number of doctor visits.
[18] http://www.who.int/choice/country/country_specific/en/index.html.

inpatient days, broken down by type of facility (clinic and hospital[19]) and by public vs. private; these data allow us to estimate $\bar{c}_k$ for the six subsectors for all WHS countries.[20] Both the inpatient and outpatient unit cost estimates exclude the costs of drugs and diagnostic tests but include the costs of personnel, capital, food and other costs. The unit costs estimates that are closest to the WHS are for 2007; we have adjusted to 2002/2003 prices using the consumer price index for the World Development Indicators. The CHOICE estimates cover all six types of health service we use in the study. In the case of inpatient care, the data are for the cost of an inpatient day; we multiply the unit cost per inpatient day by the country's average length of stay (see above for details of estimation) to get the unit cost per admission, from which we get the unit subsidy for a hospital admission, c_k-f_{ki}.

3.4 NHA data

Where available, we use NHA data to estimate aggregate costs, C_k, aggregate fees, F_k, and aggregate subsidies, S_k, for all six subsectors.[21] Our NHA data are from each country's own NHA or from multi-country NHA exercises, such as those of the OECD and EuroStat. Even a full NHA does not seek to go down to the level

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[19] We used WHO-CHOICE estimates corresponding to second-level hospitals across all countries. This might lead us to overestimating the pro-poorness of GHE, since first-level hospitals, which are likely to see more poor people than second-level hospitals, will be end up being treated in our data as if they are bigger recipients of subsidies than they really are.

[20] The WHO-CHOICE Excel file does not have cost estimates for Zimbabwe. However, estimates for 2005 are available at http://www.who.int/choice/country/zwe/cost/en/. There are no separate values in this dataset, however, for public and private facilities so we assumed the same for both subsectors.

[21] We do not subdivide the government hospital sector by level (e.g. teaching hospital versus district hospital) or by coverage scheme (e.g. ministry of health versus social security scheme) as some BIA studies have done for some countries, since our individual-level and aggregate data did not allow us to do so consistently across countries and methods. Our CI's will likely be downward biased as a result, since in many countries the higher cost facilities within the government sector at each level of care are also more often used by the better off.

we require, which is a three-way classification between function (inpatient vs. outpatient), provider (public hospital, private hospital, public clinic, and private clinic), and financing agent (government vs. out-of-pocket). A full NHA will contain three two-way tables: the function-by-provider matrix, which shows spending by all financing agents combined broken down by function (inpatient vs. outpatient) and provider type (government hospital, private hospital, government clinic, and private clinic); the provider-by-financing agent matrix, which shows spending on all functions combined broken down by provider type and financing agent (general government spending vs. out-of-pocket payments); and the function-by-financing agent matrix which shows spending by all provider types combined broken down by function and financing agent.[22]

Not all NHAs are equally complete. In Table 2 we have grouped countries into six cases. In Case A, into which 13 countries fall, we have complete data in the function-by-provider and provider-by-financing agent matrices, and we are able to estimate the subsector shares using the pro rata assumption indicated in the table. Most countries (27) fall into case B where we have complete data for the function-by-financing agent matrix, but incomplete data for the other two matrices. In this case, we used descriptive information from the NHA or other sources such as the country's Health in Transition report (HiT)[23] to set some cells in the incomplete matrices equal to zero (for example, many governments do not subsidize the private

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[22] Sometimes in NHA tables, functions are referred to as "services", and financing agents as "purchasers".
[23] http://www.euro.who.int/en/about-us/partners/observatory/health-systems-in-transition-hit-series

sector), and then used the same pro rata assumption we used in Case A to estimate the subsector shares. In Case C (only the Netherlands falls into this case) there is less information in the provider-by-financing agent matrix than in Case B, and we have used a stronger pro rata assumption to estimate the subsidy shares. In Case D (3 countries), we have a full provider-by-financing agent matrix, and we used the WHS and WHO-CHOICE data to break spending down by function. In Case E (4 countries), the NHA data available do not conform to cases A-E but with descriptive information about the health system we were able to obtain estimates of the subsidy shares. Finally, in case F (22 countries) we were unable to locate a NHA with sufficiently detailed data to be able to estimate the subsector shares. Table A2 in the Appendix reports the NHA and HiT information used for each country, and whether the country is case A, B, C, D, E or F.

3.5 Feasibility of BIA approaches by country according to data availability

Figure 1 provides a decision tree that shows how to determine which methods are feasible in a particular country depending on the data available. In countries where there are household survey data on utilization and fees, a sufficiently detailed NHA is available, and there are facility data on unit costs, all methods can be used, including both variants of the CUC method. In countries that have household survey data on utilization and fees, and have facility-based unit cost data, but do not have sufficiently detailed NHA data, we can obtain estimates using the CUS method, the FPC method and the CUC method using eqn (2). Finally, where the household survey does not ask about fees but does ask about utilization, and there are good NHA data, only the CUS method can be used.[24]

Figure 2 shows for each WHS country whether a BIA can be undertaken for overall GHE using each of the CUC, CUS and FPC methods, and subsidy shares based on both macro (i.e. NHA) and micro (i.e. WHS) data; the bottom row indicates whether the method can be used with at least one of the macro or micro share data. Green indicates that a BIA can be done using the method indicated, red that the country has a WHS but the BIA cannot be done using the combination of method and share data. Table A1 in the Appendix explains for each country which data are available and which of the three methods are feasible.

3.5 Hypothesized influences on how pro-poor GHE is at the country level

Following O'Donnell et al.'s (2007) lead, we include among our potential correlates of the GHE CI: the natural logarithm of per capita GDP in 2003 in US dollars, the natural logarithm of per capita GHE, GHE as a percentage of GDP, and GHE as a percentage of THE. All are taken from the World Development Indicators (WDI). We cannot test O'Donnell et al.'s hypothesis about a public-private quality differential encouraging opting out by the better off, but we can test this indirectly by correlating the GHE CI with measures of private sector opt-out. We use four variables, all constructed from the WHS data: the average CI for private-sector utilization; the average CI for fees paid in respect of private-sector care; the private-

[24] This outcome does not happen in our sample, but we include it for the sake of completeness.

sector share of total utilization; and the private-sector share of total fees.[25] Higher values of the first two point to a concentration of private-sector use and fees among the better off, while higher values of the second two point to a larger private sector in terms of volume or fees. If the opt-out hypothesis is correct, all four ought to be negatively correlated with the GHE CI: more opting out is hypothesized to help achieve a more pro-poor GHE distribution.

Taking our lead from the 2004 WDR, we explore the correlation between the GHE CI and the share of GHE spent on hospitals, and the share of government facility revenues coming from user fees. The former is taken from the NHA data where available, and otherwise from aggregates constructed from the WHS and the WHO-CHOICE microdata. The latter is computed from the WHS data. To capture the quality of governance, we use the data from the Worldwide Governance Indicators (WGI) project (Kaufmann et al. 2009). This uses a method similar to Principal Components to map indicators from 31 data sources into six indices capturing six different aspects of governance. The "Voice" index measures the extent to which citizens are able to participate in the selection of governments, and includes a number of indicators capturing various aspects of the political process, civil liberties and political rights, as well as indicators measuring the independence of the media. The "Political Stability" index combines indicators that measure

[25] To get the average CIs for utilization and fees in the private sector, we average the relevant CIs for inpatient care in a private hospital, outpatient care in a private hospital, and outpatient care in a private clinic. To get the private-sector share of total utilization, we sum the private-sector utilization rates and express this as a percent of the total utilization rate. We do the same for fees. The latter is somewhat more satisfactory than the former in the context of the WHS given we observe the amount of fees paid but only whether utilization occurred; in both cases, the respondent can provide data for only one subsector.

perceptions of the likelihood that the government in power will be destabilized or overthrown by possibly unconstitutional and/or violent means. The "Government Effectiveness" index combines perceptions of the quality of public service provision, the quality of the bureaucracy, the competence of civil servants, the independence of the civil service from political pressures, and the credibility of the government's commitment to policies. The "Regulatory Quality" or "Regulatory Burden" index measures the incidence of "market-unfriendly" policies such as price controls or inadequate bank supervision, as well as perceptions of the burdens imposed by excessive regulation in areas such as foreign trade and business development. The "Rule of Law" index includes indicators that capture the extent to which citizens and firms have confidence in and abide by the rules of society, including perceptions of the incidence of violent and non-violent crime, the effectiveness and predictability of the judiciary, and the enforceability of contracts. Finally, the "Control of Corruption" or "Graft" index measures perceptions of corruption, and reflects things like the frequency of "additional payments to get things done" and the effects of corruption on the business environment.[26] These data have been updated annually since 1999, and have been used to explore the links between governance and GDP per capita (cf. e.g. Kaufmann et al. 1999; Kaufmann and Kraay 2002).

[26] http://info.worldbank.org/governance/wgi/index.aspx#home

3.6 Computational issues

Five issues are worth highlighting. First, the first variant of the CUC method (based on eqn (2)) does not guarantee nonnegative imputed subsidies. In our implementation of this variant of the CUC assumption, we follow previous authors (cf. e.g. O'Donnell et al. 2007) and set negative imputed subsidies equal to zero. Second, the WHS user share for private subsectors is sometimes too low to calculate their CI. In such cases, we replace the private subsector's CI by the public subsector's CI in order to allow for the computation of aggregate CIs.[27] This imputation strategy has only a marginal effect on the aggregate CIs calculated, as the shares of the private subsectors involved are almost negligible. Third, since in some of the WHS countries there are a relatively large number of repeated values of per capita expenditure, we compute the concentration index using the extension of Kakwani et al.'s (1997) grouped-data approach proposed by Chen and Roy (2009).[28] Fourth, we estimate standard errors for the CI's using bootstrapping using the svy bootstrap Stata command with 500 replications. Resampling was performed in a manner consistent with the survey design by using sample weights and clustered stratified drawing with replacement. Not all WHS countries used primary sampling units or strata in their survey design; in addition, the sub-sample analysis did not always allow us to make full use of the survey design and resampling was

[27] We use this imputation strategy for outpatient visits in private hospitals in the case of Australia, Bosnia and Herzegovina, Croatia, Latvia, Mauritius, Russia and Swaziland, and for inpatient visits in private hospitals in the case of Croatia.

[28] We use the Stata routine 'concindc' written by Zhuo (Adam) Chen of the US Centers for Disease Control and Prevention.

simplified.[29] Fifth, we also estimate standard errors for averages and correlations that involve estimated CIs. To estimate such standard errors, we use a two-stage resampling strategy with 500 replications. The first stage follows a Monte Carlo approach that consists of randomly drawing the CIs from independent normal distributions centered on the estimated CIs and with standard deviations set at the standard errors that were estimated for the CIs. The second stage follows a simple bootstrap approach that consists of randomly drawing countries with replacement so that to obtain a sample of identical size as the original. Relevant mean CIs and correlations are computed at each iteration, and their bootstrapped standard errors are computed under the normal assumption.

4. Results

4.1 Pro-poorness of GHE by subsector on average

We ask first how the estimated *average* degree of pro-poorness of GHE within a specific subsector varies according to the BIA estimation method used. In the case of the CUC assumption we show the results obtained using eqn (2) (which makes use of facility unit cost data) and eqn (3) (which makes use of NHA aggregates). Figure 3 (see also Table A3 in the Appendix) shows that in three of the six subsectors, and on average, the CUC assumption is most pro-poor, and the FPC assumption least pro-poor; the CUS assumption in these cases lies somewhere in

[29] Countries for which no strata were used in the bootstrap include: BiH, Hungary, Kenya, Malawi, South Africa and Spain. Countries for which no primary sampling unit was used in the bootstrap include: Bangladesh, BiH, Burkina Faso, Chad, China, Congo Rep., Cote d'Ivoire, Ecuador, Finland, France, Georgia, Ghana, Hungary, Ireland, Kenya, Laos, Latvia, Malawi, Mali, Morocco, Namibia, Paraguay, Russia, Senegal, Slovakia, South Africa, Spain, Swaziland, Tunisia, Uruguay, Vietnam and Zimbabwe.

between the other two. These results, which are consistent with the results in Wagstaff (2012), suggest that the method used does indeed make a difference to the estimated degree of pro-richness and pro-poorness, and indeed whether a subsector is estimated to be pro-rich or pro-poor. There is, however, a caveat, namely that, as Figure 4 shows (see also Table A3 in the Appendix), some confidence intervals are quite large due to the relative small number of countries available for this comparison (26) and large cross-country variability.

One of the limitations of the WHS that we flagged earlier is that the questionnaire was designed such that information on outpatient care would be collected only from those respondents not reporting an inpatient admission. Most countries followed the prescribed skip pattern in the majority of cases, with 58 countries following it in at least 90 percent of cases. One concern is that those not receiving inpatient care are not a random subsample of the surveyed population, and that the concentration indices of utilization and fees are biased. Fortunately, we can test this hypothesis because three countries – Mexico, Slovenia and the Philippines – mostly chose to ignore the skip pattern: Mexico in 84 percent of cases, Slovenia in 86 percent of cases, and the Philippines in 97 percent of cases. For these countries we compared the GHE CI obtained using all the available data (the approach we use as our main approach throughout the paper) with the GHE CI we get when we fully 'enforce' the intended skip pattern by setting outpatient utilization and fees at missing for all those reporting inpatient admissions. Figure 5 shows the results. Our regular results are labeled 'original' and the values obtained when the skip pattern is fully enforced are labeled 'alternative'. The scatter plots compare the two sets of GHE CIs for all six subsectors, as well as for the subtotals and the total, using the three different imputation methods and the NHA and micro GHE data. The results are remarkably similar suggesting that adherence to the skip pattern by the majority of countries did not compromise our GHE CIs for outpatient visits.

We argued in section 2.1 that the CUS assumption is more plausible than the CUC assumption, and that the FPC assumption is probably too strong. We also noted that the CUS method has the merit of being less demanding in terms of data requirements. For both reasons, our analysis in what follows focuses on the CUS results.

We ask next how different subsectors fare, on average, in terms of their targeting of GHE toward the poor. Looking at the average values of the concentration indices across 69 countries, we see in Figure 6 that outpatient care in a government clinic emerges as the subsector where GHE is most pro-poor; in fact, it is the only subsector to emerge with pro-poor GHE. Government facilities emerge as more pro-poor (or less pro-rich) than their private counterparts, which all emerge as significantly pro-rich. The large confidence intervals around the average concentration index estimates in Figure 6 are, however, worth noting (see also Table A4 in the Appendix).

4.2 Pro-poorness of GHE by broad subtotals on average

To get a sense of how GHE is pro-poor, on average, at the level of the broad subtotal (e.g. inpatient care), we need – in addition to *concentration index* estimates for each subsector – estimates of the *share* of GHE going to each subsector, cf. eqn (7). Figure 7 contains scatter plots for each subsector of the NHA subsidy share against the micro share based on the WHO CHOICE unit cost estimates and the data on out-of-pocket spending from the WHS. Two points emerge. First, most GHE goes to government facilities – the share going to private facilities is very small in almost all countries and zero in many. Within the part of GHE that goes to government facilities, most goes to government hospitals for inpatient care. The second point to take away from Figure 7 is that the correlations between the NHA and micro shares are quite low, suggesting, on the face of it, that concentration index estimates for subtotals and for total GHE are likely to differ considerably depending on whether NHA or micro shares are used.

In fact, this is not the case. Figure 8 shows a scatter plot of the concentration indices derived using the micro weights (the x-axis) and the NHA weights (the y-axis) for each subtotal and for total GHE. The sample consists of the 29 countries for which we have been able to estimate both sets of concentration indices for all four subtotals and for total GHE. Also shown in Figure 8 are the correlation coefficients. In each panel, the results are quite similar, and are certainly much more similar than one would have guessed looking at the scatter plots of the NHA shares against the micro shares in Figure 8. Evidently, the cross-country variation in the concentration indices for the subtotals is being driven more by the variation in the subsector concentration indices than by the variation in the shares of GHE going to each subsector. Given the similarity between the two sets of results for those countries for which we have both, in the analysis that follows for the subtotals and total GHE, we use NHA shares where we have them and micro shares where we do not.

Figure 9 shows the point estimates and confidence intervals for the mean concentration indices for the four subtotals and for total GHE, using the NHA shares where available and the micro shares otherwise (see also Table A5 in the Appendix). This expands the sample to 66 countries compared to the 29 countries in Figure 8. On average, GHE on inpatient care and GHE on outpatient care emerge as mildly pro-rich, but only in the latter case is the mean concentration index significantly different from zero. By contrast while GHE on public facilities emerges as not significantly different from zero on average, GHE on private facilities emerges as significantly pro-rich. It should be stressed, though, that in these countries the share of GHE going to the private sector is quite small. On average, across these 66 countries, GHE overall is significantly pro-rich at the 95 percent level.

4.3 Pro-poorness of aggregate GHE by country

The confidence intervals for the mean concentration indices for total GHE in Figure 9 reflect two things: the cross-country variation in the pro-poorness of GHE overall; and sampling variability. Figure 10 shows for each of the 66 countries in

Figure 9 the estimate of the concentration index for GHE overall, along with the 95 percent confidence interval. The countries are shaded according to where they fell – at the time of the WHS – into the World Bank income groupings.[30] As in Figure 9, the subsector concentration indices are estimates using the CUS method, and weighted using the NHA shares where these are available and using the micro shares otherwise.

Figure 10 shows that in 39 percent (26) of the 66 countries, GHE is either significantly pro-rich or significantly pro-poor at the 95 percent level.[31] GHE is significantly pro-rich at the 95 percent level in 20 countries, namely: Brazil, Burkina Faso, Chad, China, Comoros, Côte d'Ivoire, Georgia, Ghana, Guatemala, India, Lao PDR, Mauritania, Myanmar, Nepal, Pakistan, Paraguay, Philippines, Spain, Vietnam and Zimbabwe. By contrast, GHE is significantly pro-poor at the 95 percent level in only 6 countries, namely: Ecuador, Germany, Malaysia, Namibia, South Africa and Sri Lanka. Figure 11 maps our results. Countries with no data are shaded gray, countries with statistically insignificant GHE concentration indices are shaded tan, countries with significantly pro-rich GHE distributions are shaded red, and countries with significantly pro-poor GHE distributions are shaded green. In most of the Asian countries for which we have data, GHE is either significantly

[30] http://data.worldbank.org/about/country-classifications

[31] It might be argued that the large variation in sample size across WHS countries (see Table A1 in the Appendix) makes the use of a single significance level inappropriate. We therefore explored the sensitivity of our results to standardizing each country's p-value for a sample size of 100 (cf. e.g. Good 1992). On this more demanding yardstick, five countries no longer had significant concentration indices at the five percent level: Ecuador, Germany, Mauritania, Pakistan and Zimbabwe. The unstandardized p-values of all five countries are between 0.02 and 0.05, and none has a particularly small sample size by WHS standards that could help 'justify' its relatively large unstandardized p-value.

pro-rich or (less likely) significantly pro-poor. Malaysia and Sri Lanka both emerge with significantly pro-poor GHE distributions, while China, India, Lao PDR, Myanmar, Nepal, Philippines and Vietnam all emerge with significant pro-rich GHE distributions. O'Donnell et al. (2007) also found pro-poor distributions in Malaysia and Sri Lanka, and pro-rich GHE distributions in China, India, Nepal and Vietnam. Most of the African countries with significant GHE concentration indices have pro-rich distributions of GHE, but Namibia and South Africa are exceptions, presumably because in these countries the better off make heavy use of the private sector at their own expense or through private health insurance; Burger et al. (2012) also found pro-poor GHE in South Africa. Latin America emerges as mostly pro-rich in both social health insurance (SHI) countries (recall that in this study GHE includes spending channeled through SHI institutions) and Brazil which has a NHS type system. Much of Europe and Central Asia is neither significantly pro-poor nor pro-rich: Georgia and Spain are significantly pro-rich, while Germany is the only country in the region with a significantly pro-poor GHE distribution.

4.4 Sources of cross-country variation in the pro-poorness of GHE

Figure 12 shows that the pro-poorness of GHE is significantly and positively correlated with per capita GDP and per capita GHE, and with GHE expressed as a share of GDP and total health expenditure. These findings are consistent with O’Donnell et al.’s (2007) hypotheses.[32] We also find that GHE is significantly more

[32] O’Donnell et al. also find a significant association between pro-poorness of GHE and the log of GDP per capita and GHE as a share of GDP. They do not, however, find it to be significantly correlated with GHE as a share of

pro-poor in countries that are less reliant on user fees to raise revenues for government-run health facilities; these results are consistent with the idea that user fees deter utilization of government facilities by the poor and hence make GHE less pro-poor. However, we do not find that the CI of GHE is significantly associated with the share of GHE spent on hospitals.

We fail to find any support for the opt-out hypothesis: in Figure 13 GHE is *not* significantly more pro-poor in countries with large private sectors (although the correlation has the 'right' sign), and GHE is not significantly more pro-poor in countries where the better-off make disproportionate use of – or spend disproportionately on – the private sector (if anything, in fact, the opposite is true). Finally, we find in Figure 14 correlations that lend support to the idea that better governed countries achieve a more pro-poor distribution of GHE: we find negative and significant correlations between the GHE CI and all six governance indicators.

5. Discussion

5.1 Generalizing to the world as a whole

The question arises as to where countries *not* covered by the WHS might fit into our charts. We compared the WHS countries and non-WHS countries in terms of the log of GDP per capita, the log of GHE per capita, GHE as a percentage of GDP, GHE as a percentage of total health expenditure, and the WGI governance

total health spending. The two sets of results are hard to compare: their results are *partial* correlations from a multiple regression that includes all three variables as well as regional dummies.

indicators (see Table A6 in the Appendix). The WHS and non-WHS countries have significantly different mean values on all of the governance indicators, with the WHS countries having better governance indicator scores. If we compare across all countries with data, the WHS and non-WHS countries are not significantly different on average in terms of the log of GDP per capita, the log of GHE per capita, GHE as a percentage of GDP, and GHE as a percentage of total health expenditure. However, if we restrict the comparison to the 165 countries that have data for all these variables and for all the WGI indicators, the WHS countries and the non-WHS countries look different also on the log of GDP per capita, the log of GHE per capita, and GHE as a percentage of GDP: the WHS countries are richer, have higher levels of GHE per capita, and have higher shares of GDP going to GHE.

If the correlations observed in the WHS countries apply equally to the non-WHS countries, the implication is that in countries without a WHS GHE is likely to be even more pro-rich than it is in the WHS countries. Our results, in other words, are likely to present an overly optimistic assessment of the global picture: in the world as a whole, GHE seems likely to be even less pro-poor than in the WHS countries.

5.2 Why the incidence of GHE varies by country – toward a coherent story

The scatter plots in Figures 12 and 13 are, of course, only correlations. But together they suggest a story about how the pro-poorness of GHE might be determined.

One part of the story begins with governance. There is a direct channel by which governance affects the pro-poorness of GHE: better governance increases the accountability of policy makers to voters, and of providers to policy makers. Both result in the health system being designed and managed in ways that are conducive to the poor benefitting from it – reductions in leakage of government funds as they are sent from the center to the periphery, less pilfering of drugs by health facility staff, and so on.

The second part of the story revolves around rising per capita incomes. This may also be partly a story about governance, since it is not just that better governance is *correlated* with higher per capita income (in our data, the correlations in our data range from 0.76 to 0.91, all with p-values less than 0.001); rather better governance, according to Kaufmann et al. (1999) and Kaufmann and Kraay (2002), who use the same WGI indicators, *causes* higher per capita income. Whether the result of better governance or not, we think that it is plausible that higher per capita incomes lead to a higher level of GHE, allowing the government to rely less on user fees in its facilities; this, in turn, raises utilization disproportionately among the poor, making GHE more pro-poor. The correlations in our data are consistent with this chain of events: the correlation between the logs of GDP per capita and GHE per capita is 0.99 ($p<0.001$) with a coefficient of 1.13; the correlation between the log of GHE per capita and user fees as a share of government facility revenue is -0.56 ($p<0.001$); and as Figure 12 shows the correlation between the share of government facility revenues coming from user fees and the GHE CI is 0.34 ($p<0.005$).

We know of no direct evidence suggesting the first of these correlations reflects a causal relationship. There is, however, indirect evidence: the literature suggests higher per capita incomes cause higher levels of *total* health spending (Gerdtham and Jönsson 2000; Costa-Font et al. 2011; Acemoglu et al. 2012), although the elasticity may not be above one so that rising incomes do not cause the *share* of the income spent on health to rise. And it is known that per capita income is positively correlated with GHE as a share of total health spending (Musgrove et al. 2002). Nor do we know of any evidence – direct or indirect – that the correlation between GHE per capita and user fees as a share of government facility revenue reflects a causal relationship; in fact, as far as we know, no study has previously documented this association. It is, however, perfectly plausible; in fact, it would be rather surprising if it were *not* the case. We are on firmer ground with the last link in our proposed chain of events, namely that reduced reliance on user fees raises utilization disproportionately among the poor: this is consistent with studies finding that the poor are more sensitive to user fees than the better off (cf. e.g. Gertler et al. 1987).

5.3 Limitations of the study

Among the various criticisms that might be leveled at our study, two concern methodology. One is that we examine the distribution of *subsidies*, i.e. the part of the cost of utilization that is borne by the taxpayer rather than the user. A more correct description of our study – and most BIA studies – would therefore be *subsidy incidence analysis*. An alternative approach would be to try to estimate the distribution of *welfare* associated with subsidies, by, for example, computing the distribution of compensating variations (cf. e.g. Younger 2003). We leave this as a future research exercise, but in the meantime take some comfort from the fact that Younger's (2003) results on secondary schooling in Peru change very little when he switches from the standard BIA approach to estimating the distribution of compensating variations. A second potential criticism of our study is that like most BIA studies we have conducted what is sometimes called a "standard" BIA rather than a "marginal" BIA; some argue the latter is the more policy-relevant of the two exercises (cf. e.g. Lanjouw and Ravallion 1999). Younger (2003) argues this comparison is misleading: both types of exercise indicate what would happen to the distribution of subsidies if there were a policy change; it is just that the standard BIA is relevant only to policy changes that result in a proportional scaling-up or scaling-down of subsidies across the income distribution.[33] Moreover, the objective of a cross-country comparative BIA such as this is not so much to indicate how the distribution of subsidies would change in different countries if a specific type of policy were to be implemented but rather to shed light on how and why countries vary in the degree to which GHE disproportionately benefits the poor. That said, we

[33] What policy changes would and would not do this is dependent on which of the three assumptions comes closest to capturing reality. Suppose, for example, that the FPC assumption is correct, and the policy maker simply changes the proportion of the cost the user pays as a fee. Then the new subsidy CI would be the same as the old one. By contrast, if either of the other two assumptions is correct, a policy change on fees without any change in cost would *not* leave the distribution of subsidies unchanged. Given this, it is not clear that Younger is correct when he writes: "an obvious example of such a policy change is a tax or subsidy that changes an existing price proportionately" (Younger 2003 p91).

concede that a comparative BIA analysis using the marginal BIA approach would not be uninteresting. Again, we leave this as a future research exercise, and in the meantime take some comfort from the fact that Younger (2003) obtains quite similar results in his analysis of results on secondary schooling in Peru when he switches from a standard BIA to a marginal BIA.

Another set of potential criticisms of our study concern our data. We have used original household survey microdata, and have used the same survey instrument (the WHS) in each country. Working with the raw microdata and with the same survey instrument in each country has a lot to commend it, providing of course that the instrument is a good one. The WHS has many strengths not least the fact it contains information on the key BIA variables in most countries. But it is not without its limitations. For a start, it was conducted 10 years ago so our results predate many important recent health system reforms, including those inspired by the worldwide push toward universal health coverage (UHC). Our results can be thought of as a baseline that – combined with future studies – will allow analysts to examine the changes that have occurred in the pro-poorness of GHE since these UHC reforms. In any case, this study provides a uniquely homogeneous measurement of GHE incidence across countries, which enables us to produce general results on how various BIA methods compare to each other, and on which country level factors are correlated to pro-poorness of GHE. The WHS has other limitations noted in the text: it contains information on whether inpatient or outpatient care was received not the number of contacts; the information on whether a facility used was public or private, and the name of the facility, is only for the last facility visited, and in seven countries was missing; it asks about outpatient care use only among people who had not received inpatient care; it asks about fees only in 55 countries and only about fees paid to the last-visited facility; and the consumption questions are very few in number compared to a multipurpose household survey. Not all of these limitations are as major as they might at first seem: for example, we found in the three countries where data on outpatient care were collected from everybody (irrespective of whether they had been admitted to hospital) that the results were similar whether or not we imposed the intended questionnaire skip pattern.

Our ancillary data – the NHA and microdata that we use to get the aggregates in eqn (3) and the GHE shares in eqn (7) – might also be criticized. It came as a surprise to us that despite over 30 years of activity on National Health Accounts[34] only 13 of the 69 WHS countries[35] have the NHA data needed to derive such basic information as the amount of GHE going to the six core subsectors of the health sector, and that 20 countries either have no NHA (19) or have one but have insufficient data in the three core NHA matrices to make even an educated guess as to the GHE going to each of the subsectors. Surprisingly, these 20 countries include three OECD countries (Ireland, Italy and the United Kingdom), as well as three of

[34] In Google Scholar we found two publications from the early 1980s with "National Health Accounts" in the title, and a total of 225 cited publications with "National Health Accounts" in the title. Google's Ngram Viewer shows that the expression "National Health Accounts" starting to appear in 1983 with growth in use of the term from 1991.
[35] We exclude the 70th country (Turkey) from this count since its WHS does not include utilization data.

the BRICS countries (Brazil, India and the Russian Federation); many far poorer countries are much further ahead than these comparatively prosperous countries in terms of NHA data. The microdata that we use to plug the large gaps left by the incomplete NHA data are also not ideal. The WHS allows us to get a reasonably good estimate of the population inpatient admission rate and average length of stay, but not of the population outpatient visit rate. It also came as a surprise to us that finding international data on the population outpatient visit rate is so hard, and that different sources are so often inconsistent with one another; our regression-based estimates are not perfect, but they are the best we can come up with. By contrast, thanks to the WHO-CHOICE initiative (Adam et al. 2003), obtaining unit cost estimates for all countries was straightforward, though of course the data are largely modeled.

6. Conclusions

Our findings can be summarized as follows. First, like Wagstaff (2012), who presented theoretical results illustrated by empirical results for one country, we find that the method used to impute subsidies at the individual level does indeed make a difference to the estimated degree of pro-richness or pro-poorness of a specific subsector, and indeed whether the subsector emerges as pro-rich or pro-poor. On average, we find that the constant unit cost (CUC) assumption results in the most pro-poor results, while the fees-proportional-to-cost (FPC) assumption results in the least pro-poor results; the constant unit subsidy (CUS) assumption lies somewhere between the other two assumptions. Since CUS is both arguably the most plausible of the three assumptions and offers the practical advantage of requiring data only on utilization (in addition to the individual's rank in the income (or consumption) distribution at the subsectoral level), we based all other cross-country comparisons on this assumption. Second, outpatient care in a government clinic emerges as the subsector where GHE is most pro-poor on average; however, in no government subsector does GHE emerge as significantly pro-poor on average. By contrast, GHE going to all types of care delivered in private facilities emerges as significantly pro-rich. Third, despite National Health Accounts (NHA) exercises in a large number of countries, we found it very hard to find the shares of GHE going to each subsector that we needed to compute the incidence of GHE overall and GHE to aggregates of subsectors (e.g. government facilities). Where we were unable to find the shares from a NHA, we computed the shares using data on health facility unit costs, and data on fees and utilization from the household survey. It turns out that in the countries where we have both types of data, the concentration index for overall GHE was not very sensitive to the shares used. Fourth, we find that, on average, GHE on all inpatient care is pro-rich but not significantly so, while GHE on all outpatient care is significantly pro-rich. GHE in all private facilities is significantly pro-rich, on average; the caveat here is that in these countries the share of GHE going to the private sector is quite small. Overall, we find that, on average, across 66 countries, total GHE is significantly pro-rich. Fifth, we find that GHE is significantly pro-rich (at the 95 percent level) in 20 countries and significantly pro-poor in only six countries; in 40 countries (60 percent) GHE is neither significantly pro-rich nor significantly pro-poor. Most Asian countries have significant pro-rich distributions of GHE. Sixth, we find that the pro-poorness of CI at the country level is significantly and positively correlated with GDP per capita and GHE per capita, and significantly and negatively correlated with the share of government facility revenues coming from user fees. We do not find that GHE is more pro-poor in countries with large private sectors or in countries where private-sector use and out-of-pocket payments is heavily concentrated among the better off; the data are not, in other words, consistent with the opt-out hypothesis. We do find, however, that the pro-poorness of GHE is significantly and positively correlated with six measures of the quality of a country's governance. We hypothesize on the basis of these and other correlations, and supporting evidence from studies that tried to establish causal relationships, that higher per capita incomes increase the pro-poorness of GHE by facilitating higher levels of GHE and reduced reliance on user fees, and that governance affects the pro-poorness of GHE – directly by increasing the accountability of policy makers to voters and of providers to policy makers, and indirectly by raising per capita income. We also speculate that because the countries without a WHS are, on average, less well governed (and may also be poorer and have lower levels of GHE), our results probably present an overly optimistic assessment of the global picture: in the world as a whole, GHE seems likely to be even less pro-poor than it is in the countries included in our analysis.

While future studies could benefit from methodological extensions, and could benefit even more from improvements in data quality, our study does, we believe, offer some important insights. We have clarified what data are required to implement the three different BIA methods, and have shown how, in the absence of NHA data, one can build up from microdata, both in the implementation of the CUS method and in the computation of the incidence of overall subsidies. We have also shown that the method used to impute subsidies at the individual level does matter, so mixing methods in the same analysis undermines the credibility of one's results.

In addition to its methodological insights, our study provides some insights for policy. Our headline finding – that, on average, across 66 countries at all levels of per capita income, GHE is significantly pro-rich – suggests that the problem of GHE being pro-rich is not isolated to a few countries, or to countries at specific stages of development, but rather is a global phenomenon. On the bright side, the fact that we find variation across countries – even taking into account sampling variability – makes it clear that the pro-richness of GHE is not a given: GHE is not significantly pro-rich in the majority of countries (46 out of 66), and is actually significantly pro-poor in six. One policy lever available to policy makers wanting to make GHE less pro-rich is suggested by our finding that GHE spent in private facilities is significantly pro-rich: while contracting with private facilities may make GHE more efficient, our results imply that there is an equity price to be paid for doing so. The fact we find that GHE is significantly less pro-rich (or more pro-poor) in countries where the share of government facility revenues coming from user fees is relatively high suggests another policy lever, namely limiting user fees in government facilities. Linked to this is our finding that GHE is more pro-rich in countries with relatively low levels of GHE: raising GHE allows a government to reduce its reliance on user fees as a source of revenue for government facilities, but may lead to an improved distribution of subsidy incidence through other channels too. Finally, our results suggest that a more pro-poor distribution of GHE may be one of the many benefits to be had from better governance.

Table 1: Computing concentration index for subsidies under different assumptions and different data constraints

		CUC	CUS	FPC
Subsidy amounts based on NHA / macro data	Subsector specific CIs	CI_{S_k} computed from CI_{Q_k} and CI_{F_k} via eqn (3), using NHA aggregates C_k, F_k and S_k	CI_{S_k} computed from CI_{Q_k} – eqn (5)	CI_{S_k} computed from CI_{F_k} – eqn (6)
	Sector-level and overall CIs	Use NHA shares to go from CI_{S_k} to CI_S – eqn (7)	Use NHA shares to go from CI_{S_k} to CI_S – eqn (7)	Use NHA shares to go from CI_{S_k} to CI_S – eqn (7)
Subsidy amounts based on micro data on unit costs, fees and utilization	Subsector specific CIs	S_{ki} computed at individual level using c_k, f_{ki}, q_{ki} – eqn (2). Use these to compute CI_{S_k}	CI_{S_k} computed from CI_{Q_k} – eqn (5)	CI_{S_k} computed from CI_{F_k} – eqn (6)
	Sector-level and overall CIs	Compute subsidy shares from microdata on utilization rates, and average costs and fees – eqn (10). Use these to go from CI_{S_k} to CI_S – eqn (7)	Compute subsidy shares from microdata on utilization rates, and average costs and fees – eqn (10). Use these to go from CI_{S_k} to CI_S – eqn (7)	Compute subsidy shares from microdata on utilization rates, and average costs and fees – eqn (10). Use these to go from CI_{S_k} to CI_S – eqn (7)

Table 2: NHA data availability and assumptions used to estimate subsector-specific subsidy and fee shares

	Function x Provider[@]	Provider x Financing Agent[§]	Function x Financing Agent[$]	Assumption used to estimate shares of GHE and out-of-pocket spending in each of the six subsectors	Countries
Case A	Full data	Full data	Data not required	Funding source (GHE or OOP) is allocated to each provider-function (public/private hospital/clinic, and IP/OP) as the ratio of the funding source to total funding *of the provider* times the amount spent by the provider on the function.	Cote d'Ivoire, Ethiopia, Finland, Kenya, Malawi, Malaysia, Mali, Nepal, Portugal, Senegal, Spain, Uruguay, Zambia
Case B	Incomplete data	Incomplete data	Full data	Information about health system used to find which missing cells in Function x Provider table and Provider x Financing Agent table can be set to zero. Funding source is then allocated to each provider-function using Case A pro rata assumption.	Australia, Austria, Bangladesh, Belgium, China, Congo, Rep., Czech Republic, Denmark, Estonia, France, Georgia, Germany, Ghana, Greece, Hungary, Israel, Kazakhstan, Latvia, Luxembourg, Morocco, Namibia, Norway, Slovak Republic, Slovenia, Sri Lanka, Sweden, Ukraine, Vietnam
Case C	Incomplete data	Almost all data missing	Full data	Information about health system used to find which missing cells in Function x Provider table and Provider x Financing Agent table can be set to zero. Funding source is then allocated to each provider-function as the ratio of the funding source to total funding *of the function* times the amount spent by the provider on the function.	Netherlands
Case D	No data	Full data	No data	IP/OP breakdown according to WHS utilization and WHO-CHOICE unit costs	Burkina Faso, Pakistan, South Africa
Case E	Some data	Some data	Some data	Data availability does not conform to cases A-D but with information about health system, estimates can be made.	Ecuador, Lao PDR, Mexico, Myanmar
Case F	Insufficient data	Insufficient data	Insufficient data	No NHA-based share estimates possible	Bosnia and Herzegovina, Brazil, Chad, Comoros, Croatia, Dominican Republic, Guatemala, India, Ireland, Italy, Mauritania, Mauritius, Paraguay, Philippines, Russian Federation, Swaziland, Tunisia, United Arab Emirates, United Kingdom, Zimbabwe

[@] Spending by all financing agents combined broken down by type of care and provider. § Spending on all types of care combined broken down by type of provider and financing agent.
[$] Spending on all types of provider combined broken down by type of care and financing agent.

Figure 1: Decision tree for seeing what methods are possible given data availability

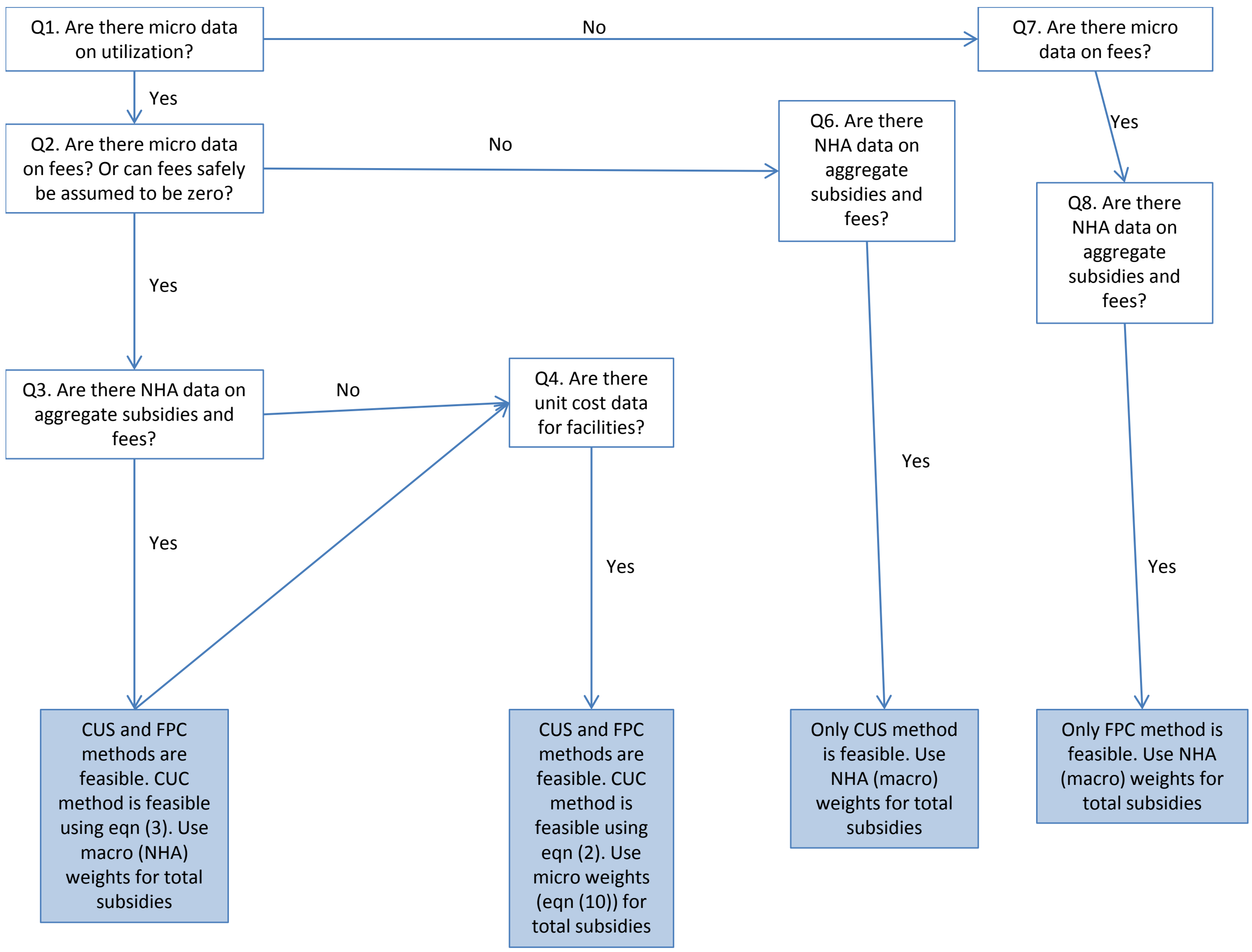


Figure 2: Feasibility of different BIA approaches for overall GHE by country

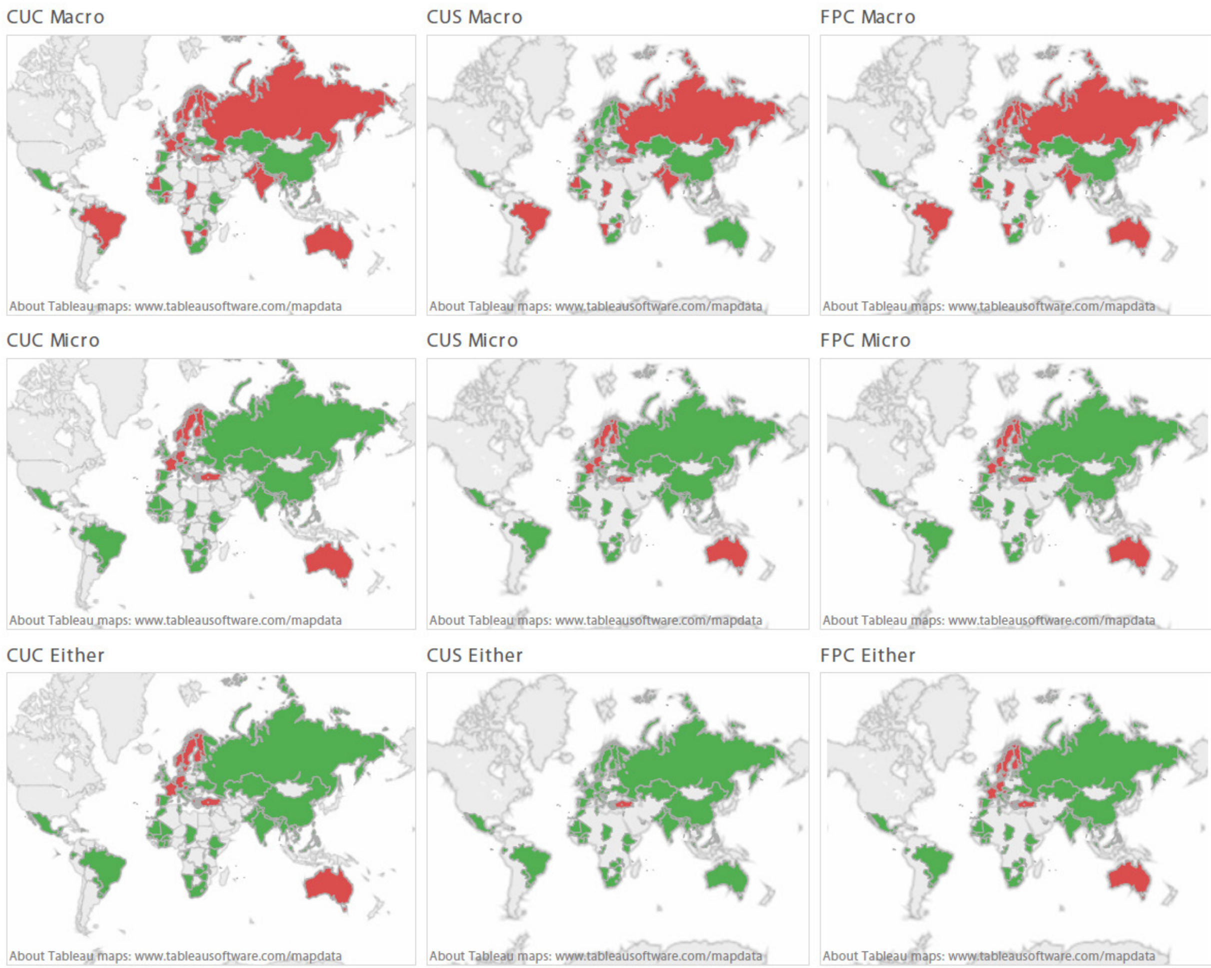
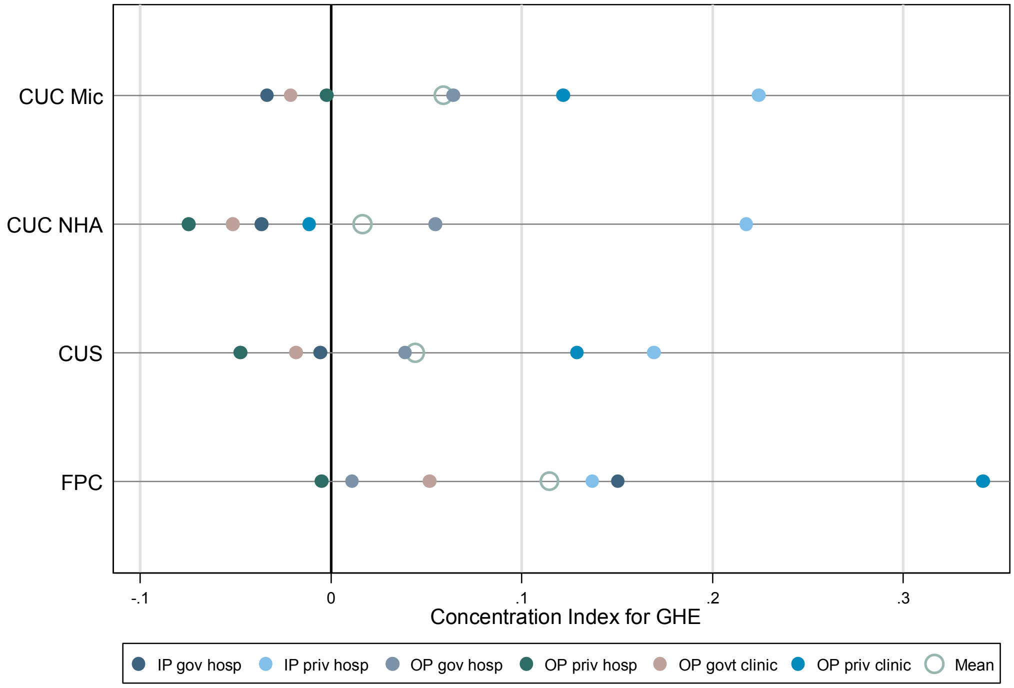
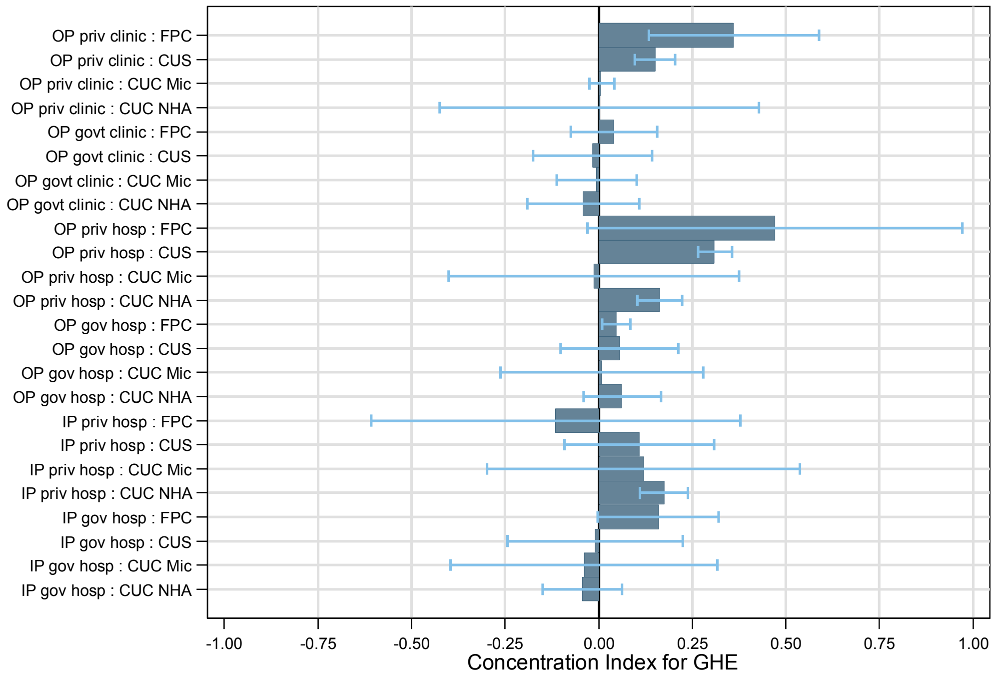


Figure 3: Mean GHE CI estimates by subsector and method



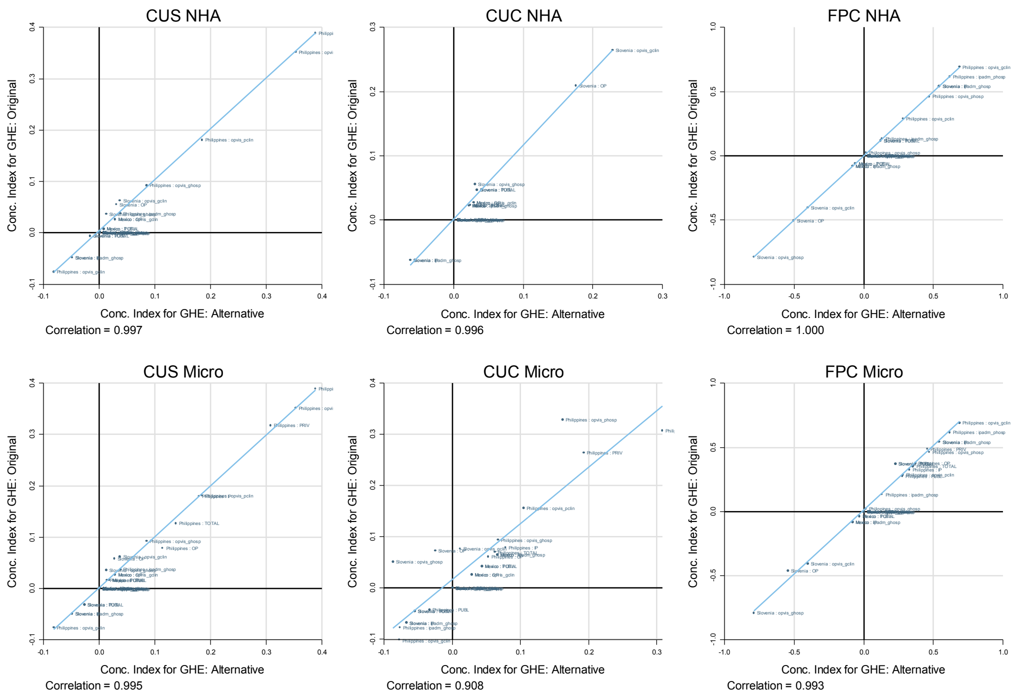
Note: Sample includes 26 countries with CIs for all 6 subsectors for all 4 methods

Figure 4: Mean GHE CI estimates and 95% confidence intervals by subsector and method



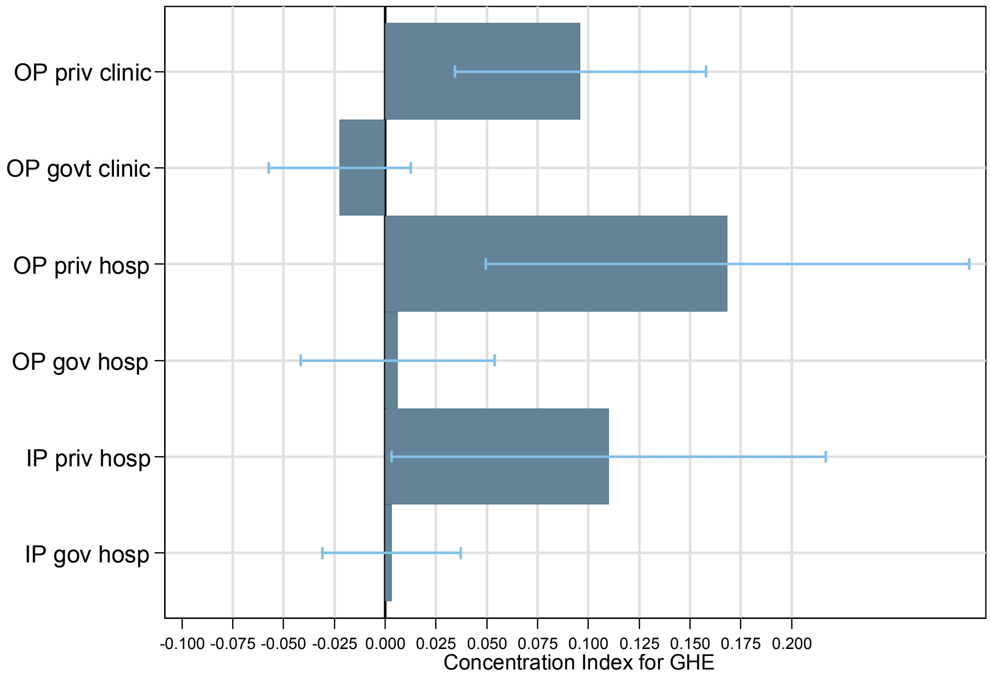
Note: Sample includes 26 countries with CIs for all 6 subsectors for all 4 methods.
Whiskers show 95% confidence interval obtained from bootstrapped standard errors

Figure 5: Sensitivity analysis to see how results are affected by observing outpatient visits only for non-inpatient users



Note: In 'original' results, all WHS data are used. In 'alternative' results, WHS outpatient data are used only when inpatient admission did not occur, per original WHS design

Figure 6: Mean GHE CI estimates by subsector



Note: CUS method. Sample includes 69 countries with CIs for all 6 subsectors
Whiskers show 95% confidence interval obtained from bootstrapped standard errors

Figure 7: NHA vs. micro shares, by subsector

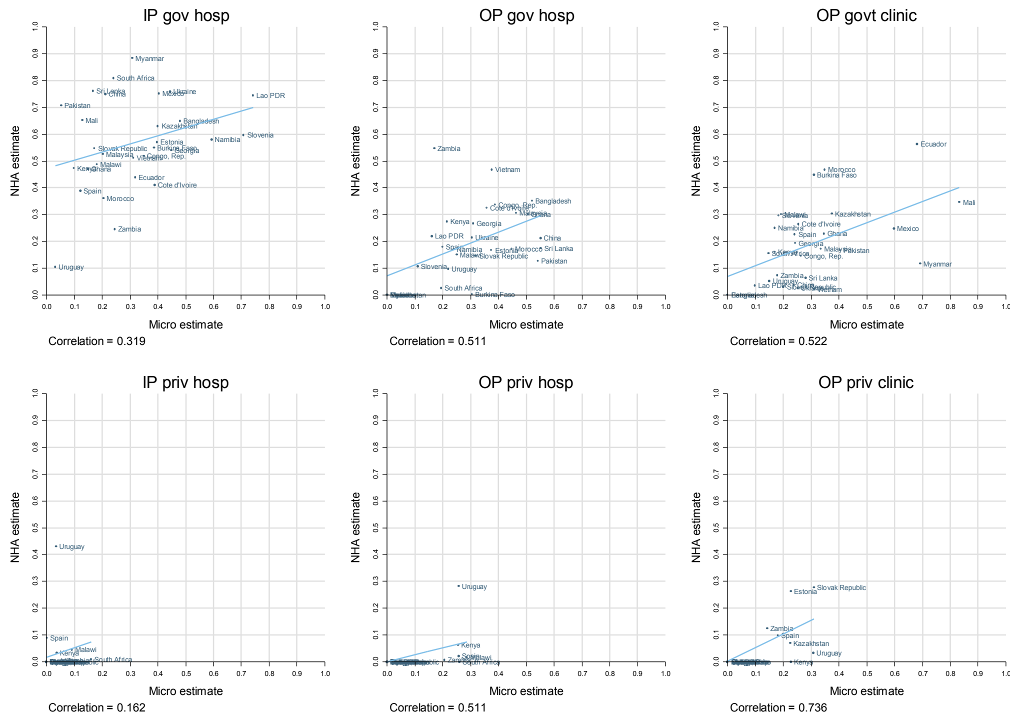
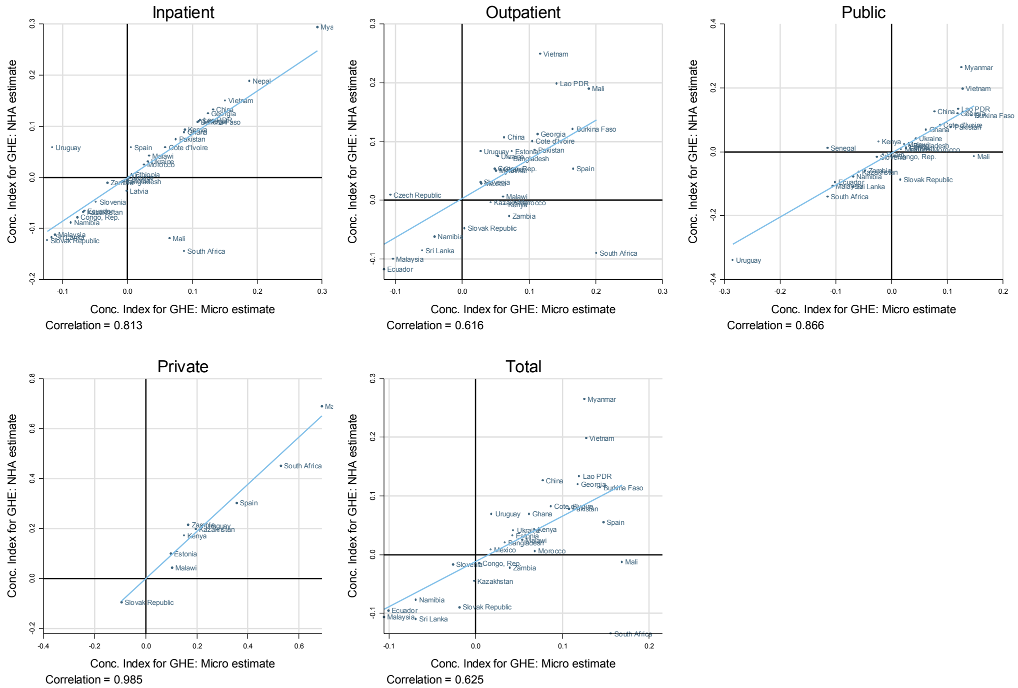
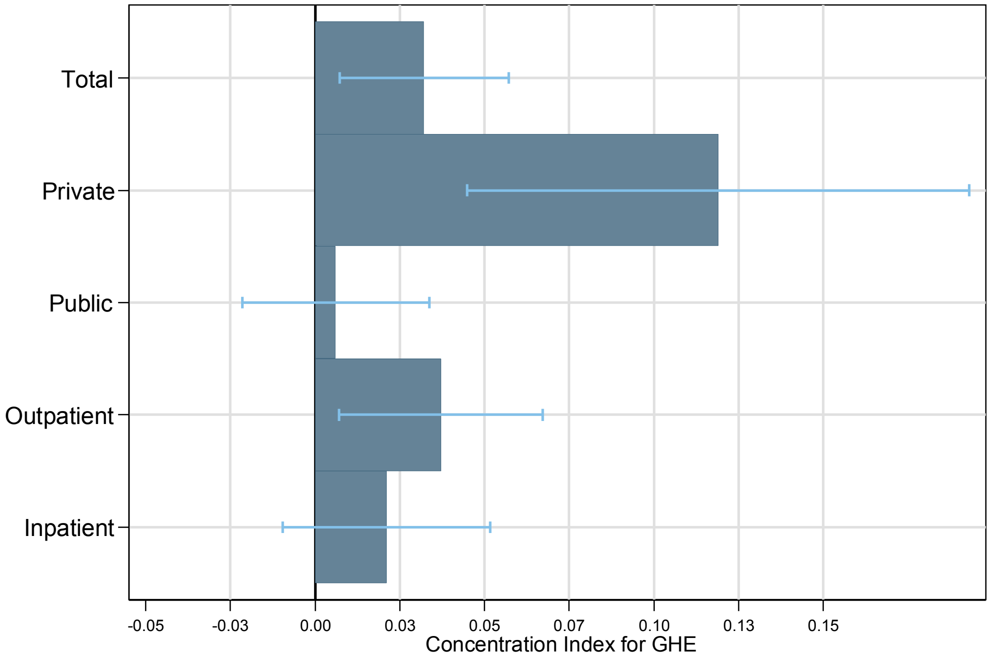


Figure 8: NHA vs. micro CIs, by subsector



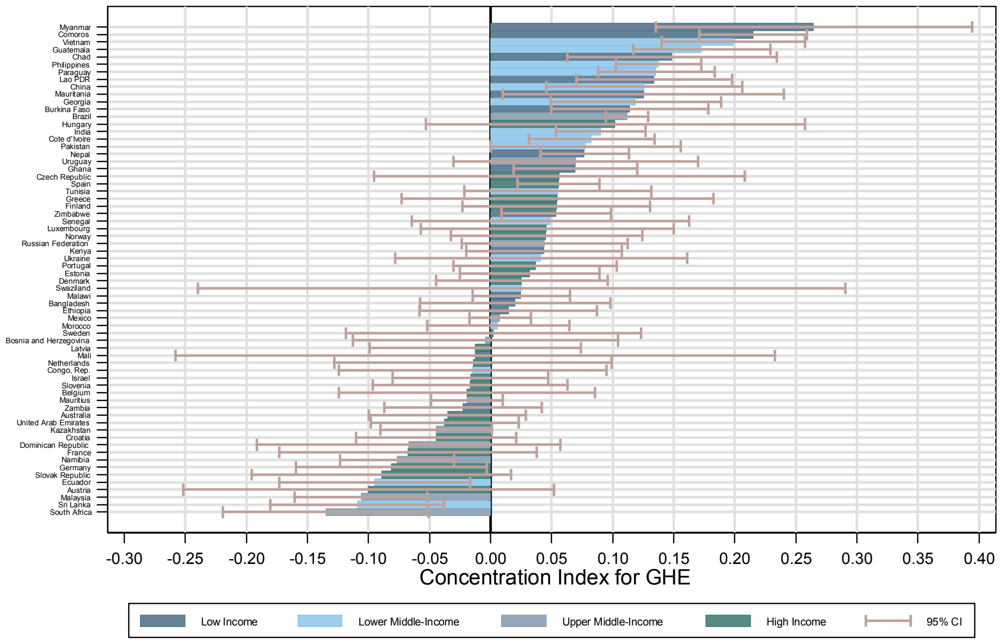
Note: CUS method. Sample includes 29 countries with CIs for all 4 subtotals and total, with both NHA- and micro-based estimates

Figure 9: Mean GHE CI estimates by subtotal



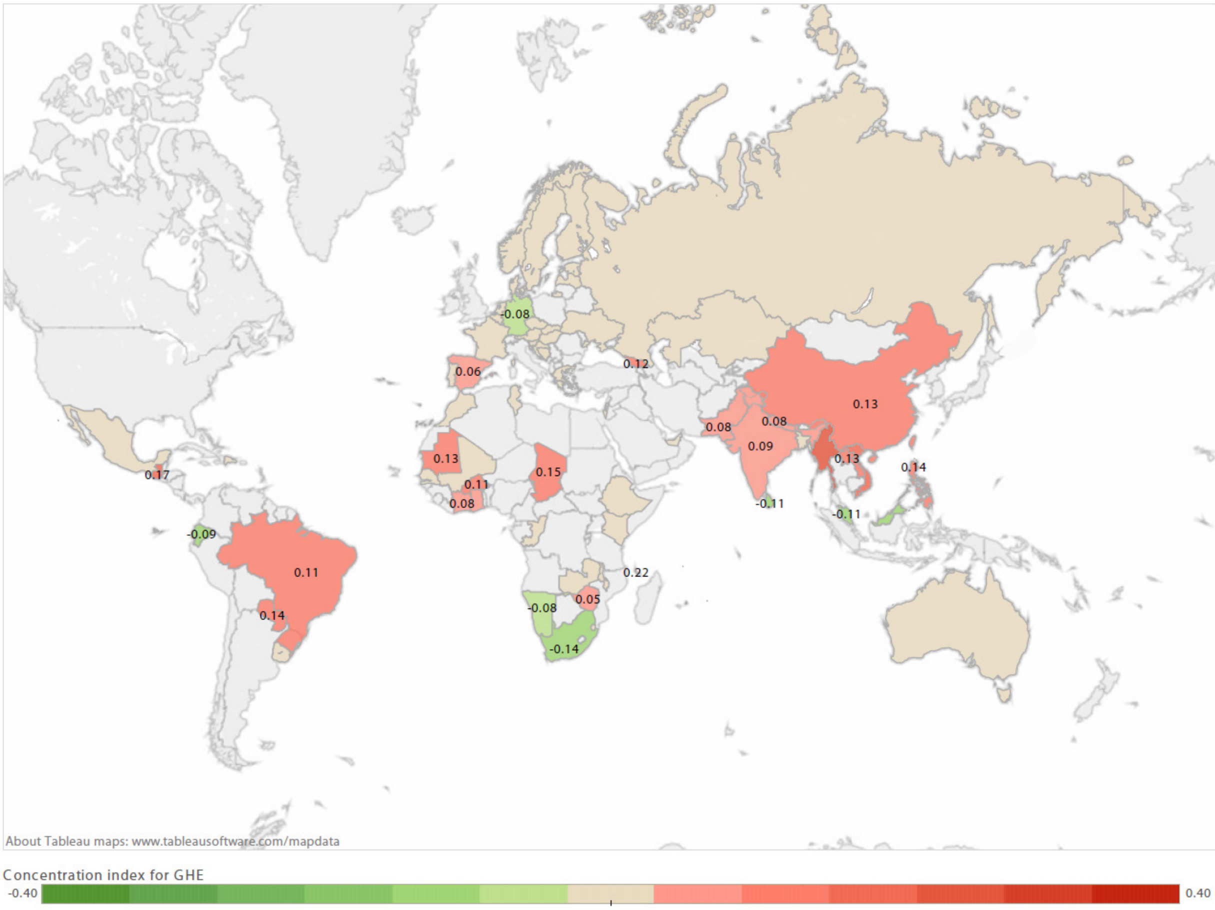
Note: CUS method. NHA unless unavailable in which case Micro used.
Sample includes 66 countries with CIs for all 4 subtotals and total.
Whiskers show 95% confidence interval obtained from bootstrapped standard errors

Figure 10: Overall GHE CI estimates, by country



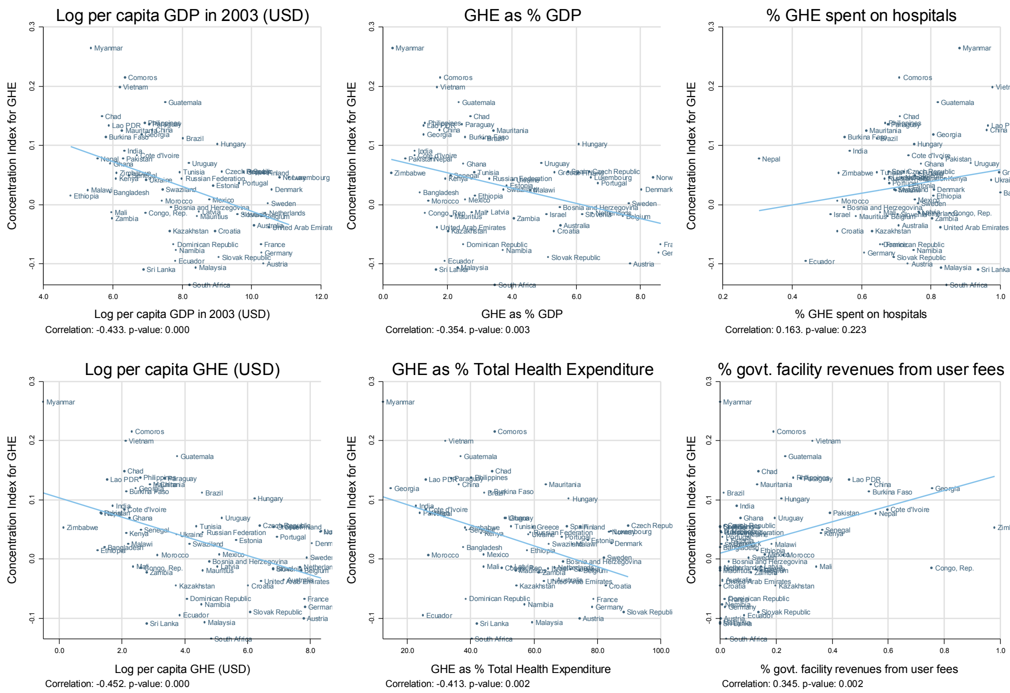
Note: Total GHE computed using CUS method. Subsector concentration indices weighted by NHA shares where available; micro shares used otherwise. Sample includes 66 countries.
Whiskers show 95% confidence interval obtained from bootstrapped standard errors.
26 of the concentration indices are significant at the 95% level

Figure 11: GHE CI by country



Note: Gray: no data. Tan: CI not statistically significant. Green: pro-poor. Red: pro-rich.

Figure 12: GHE CI vs. GDP per capita and health expenditure / financing indicators



Note: p-values based on bootstrapped standard errors. Sample includes 66 countries

Figure 13: GHE CI vs. Indicators of private-sector opt-out

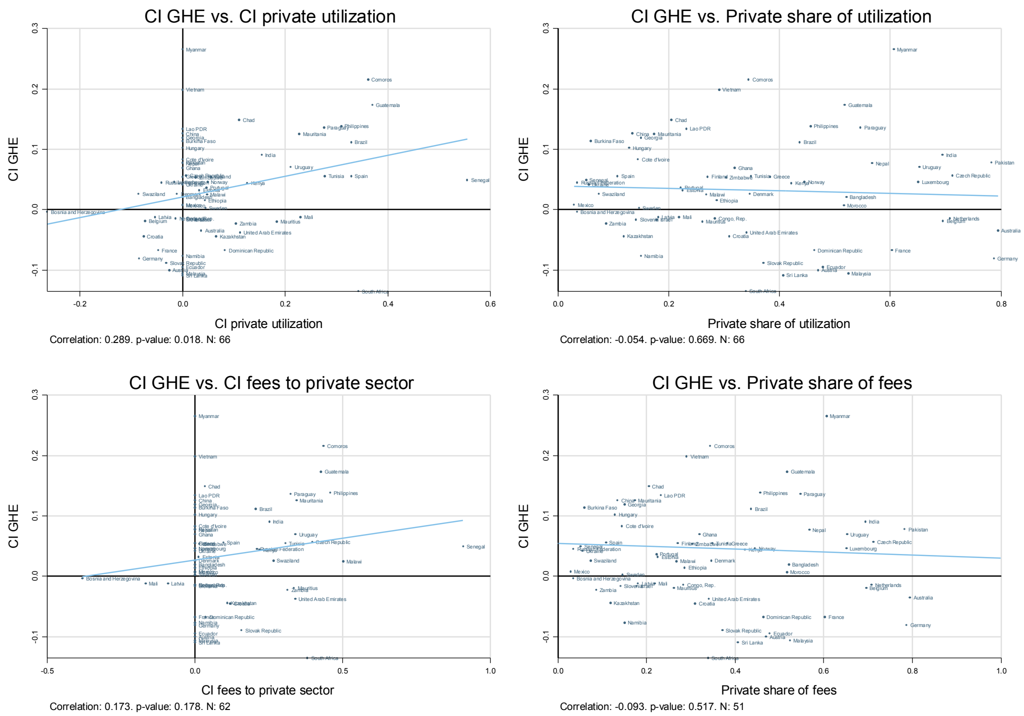
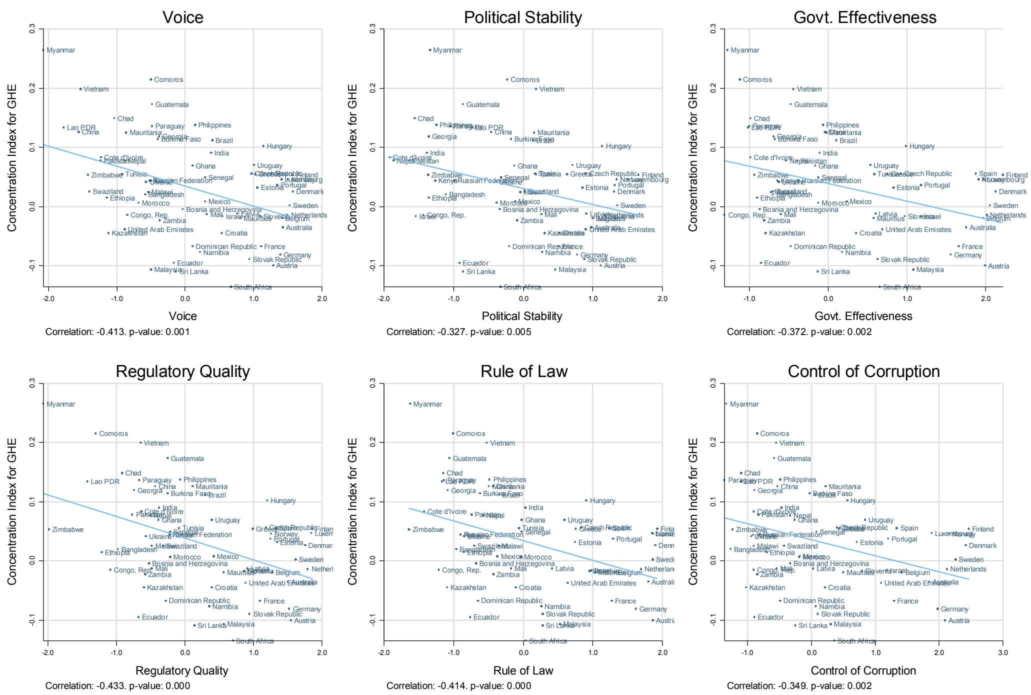


Figure 14: GHE CI vs. governance indicators



Note: p-values based on bootstrapped standard errors. Sample includes 66 countries

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Appendix

Table A1: Data availability and implied feasibility of BIA based on decision tree, by country and method

Country	WHS Sample Size	WHS includes utilization	WHS includes fees	NHA case	unit cost available	CUC is feasible	CUS is feasible	FPC is feasible
Australia	1,745	Y	N	B	Y	N	Y	N
Austria	1,055	Y	N	B	Y	N	Y	N
Bangladesh	5,929	Y	Y	B	Y	Y	Y	Y
Belgium	478	Y	N	B	Y	N	Y	N
Bosnia and Herzegovina	802	Y	Y	F	Y	Y	Y	Y
Brazil	4,900	Y	Y	F	Y	Y	Y	Y
Burkina Faso	4,912	Y	Y	D	Y	Y	Y	Y
Chad	4,438	Y	Y	F	Y	Y	Y	Y
China	3,991	Y	Y	B	Y	Y	Y	Y
Comoros	1,817	Y	Y	F	Y	Y	Y	Y
Congo, Rep.	2,706	Y	Y	B	Y	Y	Y	Y
Cote d'Ivoire	3,111	Y	Y	A	Y	Y	Y	Y
Croatia	978	Y	Y	F	Y	Y	Y	Y
Czech Republic	712	Y	Y	B	Y	Y	Y	Y
Denmark	1,002	Y	N	B	Y	N	Y	N
Dominican Republic	4,903	Y	Y	F	Y	Y	Y	Y
Ecuador	4,406	Y	Y	E	Y	Y	Y	Y
Estonia	1,015	Y	Y	B	Y	Y	Y	Y
Ethiopia	4,294	Y	Y	A	Y	Y	Y	Y
Finland	1,013	Y	N	A	Y	N	Y	N
France	1,007	Y	N	B	Y	N	Y	N
Georgia	2,751	Y	Y	B	Y	Y	Y	Y
Germany	1,257	Y	N	B	Y	N	Y	N
Ghana	4,095	Y	Y	B	Y	Y	Y	Y
Greece	999	Y	N	B	Y	N	Y	N
Guatemala	4,699	Y	Y	F	Y	Y	Y	Y
Hungary	134	Y	Y	B	Y	Y	Y	Y
India	10,208	Y	Y	F	Y	Y	Y	Y
Ireland	1,014	Y	N	F	Y	N	N	N
Israel	720	Y	N	B	Y	N	Y	N
Italy	1,000	Y	N	F	Y	N	N	N
Kazakhstan	4,497	Y	Y	B	Y	Y	Y	Y
Kenya	4,584	Y	Y	A	Y	Y	Y	Y
Lao PDR	4,972	Y	Y	E	Y	Y	Y	Y
Latvia	832	Y	Y	B	Y	Y	Y	Y
Luxembourg	700	Y	N	B	Y	N	Y	N
Malawi	5,481	Y	Y	A	Y	Y	Y	Y
Malaysia	6,011	Y	Y	A	Y	Y	Y	Y
Mali	3,953	Y*	Y	A	Y	Y	Y	Y
Mauritania	3,679	Y	Y	F	Y	Y	Y	Y
Mauritius	3,957	Y	Y	F	Y	Y	Y	Y
Mexico	38,515	Y	Y	E	Y	Y	Y	Y
Morocco	4,696	Y	Y	B	Y	Y	Y	Y
Myanmar	6,045	Y	Y	E	Y	Y	Y	Y
Namibia	4,233	Y	Y	B	Y	Y	Y	Y
Nepal	8,781	Y	Y	A	Y	Y	Y	Y
Netherlands	1,091	Y	N	C	Y	N	Y	N
Norway	826	Y	N	B	Y	N	Y	N
Pakistan	6,456	Y	Y	D	Y	Y	Y	Y
Paraguay	5,273	Y	Y	F	Y	Y	Y	Y
Philippines	10,068	Y	Y	F	Y	Y	Y	Y
Portugal	1,029	Y	N	A	Y	N	Y	N
Russian Federation	4,422	Y	Y	F	Y	Y	Y	Y

Country	WHS Sample Size	WHS includes utilization	WHS includes fees	NHA case	unit cost available	CUC is feasible	CUS is feasible	FPC is feasible
Senegal	3,107	Y	Y	A	Y	Y	Y	Y
Slovak Republic	1,737	Y	Y	B	Y	Y	Y	Y
Slovenia	666	Y	Y	B	Y	Y	Y	Y
South Africa	2,351	Y	Y	D	Y	Y	Y	Y
Spain	5,580	Y	Y	A	Y	Y	Y	Y
Sri Lanka	6,733	Y	Y	B	Y	Y	Y	Y
Swaziland	2,783	Y	Y	F	Y	Y	Y	Y
Sweden	999	Y	N	B	Y	N	Y	N
Tunisia	5,114	Y	Y	F	Y	Y	Y	Y
Turkey	1,167	N	N			N	N	N
Ukraine	1,199	Y	Y	B	Y	Y	Y	Y
United Arab Emirates	2,596	Y	Y	F	Y	Y	Y	Y
United Kingdom	2,967	Y	N	F	Y	N	N	N
Uruguay	4,171	Y	Y	A	Y	Y	Y	Y
Vietnam	4,135	Y	Y	B	Y	Y	Y	Y
Zambia	4,106	Y	Y	A	Y	Y	Y	Y
Zimbabwe	1,745	Y	Y	F	Y	Y	Y	Y
No. countries Y or A-E		69	52	49	69	52	66	52

Notes: N indicates No, Y Yes. For ‘NHA case’ code, see Table 2 in the text. * Feasibility for each method is computed using the decision tree in Figure 1 in the text.

Table A2: NHA and other information used to construct GHE by subsector

Country	Title of HNA	Other documents used	Year	Case
Australia	Health Expenditure Australia, 2007-08		2006/2007	B
Austria	OECD NHA tables		2004	B
Bangladesh	SHA-Based Health Accounts in the Asia/Pacific Region, Bangladesh, 2006		2004/2005	B
Belgium	OECD NHA tables	Health Systems in Transition, Belgium, 2010	2003	B
Bosnia and Herzegovina	N/A			F
Brazil	N/A			F
Burkina Faso	Construction des Comptes Nationaux de la Santé pour 2003		2003	D
Chad	N/A			F
China	SHA-Based Health Accounts in the Asia/Pacific Region, China, 1990-2006		2005	B
Comoros	N/A			F
Congo, Rep.	Comptes Nationaux de la Santé 2008-2009		2008	B
Cote d'Ivoire	Comptes Nationaux de la Santé, exercices 2007, 2008		2007	A
Croatia	N/A			F
Czech Republic	OECD NHA tables	Health Systems in Transition, Czech Republic, 2005	2003	B
Denmark	OECD NHA tables	Health Systems in Transition, Denmark, 2007	2003	B
Dominican Republic	N/A			F
Ecuador	Cuentas Nacionales de Salud: Ecuador, 1998		1998	E
Estonia	OECD NHA tables	Health Systems in Transition, Estonia, 2004	2003	B
Ethiopia	Ethiopia's Third National Health Accounts, 2004/05		2004/2005	A
Finland	OECD NHA tables		2003	A
France	OECD NHA tables	Health Systems in Transition, France, 2004	2004	B
Georgia	National Health Accounts For Georgia 2001-2003	Health Systems in Transition, Georgia, 2009	2003	B
Germany	OECD NHA tables	Health Systems in Transition, Germany, 2004	2003	B
Ghana	National Health Accounts, Ghana 2002		2002	B
Greece	OECD NHA tables		2003	B
Guatemala	N/A			F
Hungary	OECD NHA tables	Health Systems in Transition, Hungary, 2011	2003	B
India	N/A			F
Ireland	N/A			F
Israel	OECD NHA tables		2006	B
Italy	N/A			F
Kazakhstan	Kazakhstan NHA Report for		2010	B

Country	Title of HNA	Other documents used	Year	Case
	2010; Ministry of Health			
Kenya	Kenya National Health Accounts 2001-2002		2001/2002	A
Lao PDR	Lao National Health Accounts 2006-07		2006/2007	E
Latvia	Eurostat Health Care Expenditure Database		2005	B
Luxembourg	OECD NHA tables	Health Systems in Transition, Luxemburg, 1999	2003	B
Malawi	Malawi National Health Accounts (NHA) 2002-2004		2002/2003	A
Malaysia	SHA-Based Health Accounts in the Asia/Pacific Region, Malaysia, 1997-2006		2006	A
Mali	Les Comptes Nationaux de la Santé du Mali 1999-2004		2003	A
Mauritania	N/A			F
Mauritius	N/A			F
Mexico	OECD Matrices de Gasto en Salud, Mexico, 1999-2003		2003	E
Morocco	Royaume du Maroc Ministere de la Sante, Comptes Nationaux de la Santé 2006		2006	B
Myanmar	National Health Accounts, Myanmar, 2002-2005		2002/2003	E
Namibia	Namibia National Health Accounts 2001/02 - 2006/07; Estimate of Revenue and Expenditure for the Financial Year 1 April 2004 - 31 March 2005		2002/2003	B
Nepal	Nepal National Health Accounts, Second Round		2005/2006	A
Netherlands	OECD NHA tables	Health Systems in Transition, The Netherlands, 2010	2008	C
Norway	OECD NHA tables	Health Systems in Transition, Norway, 2006	2006	B
Pakistan	National Health Accounts, Pakistan 2007/08		2007/2008	D
Paraguay	N/A			F
Philippines	N/A			F
Portugal	OECD NHA tables		2003	A
Russian Federation	N/A			F
Senegal	Comptes Nationaux de la Santé du Sénégal, année 2005		2005	A
Slovak Republic	OECD NHA tables	Health Systems in Transition, Slovakia, 2011	2006	B
Slovenia	OECD NHA tables	Health Systems in Transition, Slovenia, 2009	2003	B
South Africa	Health financing and expenditure in post-apartheid South Africa, 1996/97 - 1998/99		1998/1999	D
Spain	OECD NHA tables		2003	A
Sri Lanka	Sri Lanka Health Account, National Health Expenditure,		2004	B

Country	Title of HNA	Other documents used	Year	Case
	1990-2008			
Swaziland	N/A			F
Sweden	OECD NHA tables	Health Systems in Transition, Sweden, 2005	2003	B
Tunisia	National Health Accounts in Tunisia: Results for Years 2004 and 2005		2004	F
Ukraine	Ukraine National Health Accounts 2003-2004, Volume 1		2003	B
United Arab Emirates	N/A			F
United Kingdom	N/A			F
Uruguay	Cuentas Nacionales de Salud en el Uruguay 2000		2000	A
Vietnam	Ministry of Health National Health Account Implementation in Viet Nam Period From 2000-2006		2006	B
Zambia	Zambia National Health Accounts 2002: Main Findings		2002	A
Zimbabwe	N/A			F

Notes: N/A indicates NHA does not appear to be available. Absence of hyperlink indicates document is not available online. For 'NHA case' code, see Table 2 in the text.

Table A3: Mean GHE CI estimates by subsector and method

	CI	se	pval	ci95_lo	ci95_up
cuc_nha					
ipadm_ghosp	-0.044	0.054	0.424	-0.150	0.063
ipadm_phosp	0.174	0.033	0.000	0.110	0.239
opvis_ghosp	0.063	0.053	0.238	-0.041	0.167
opvis_phosp	0.164	0.030	0.000	0.104	0.223
opvis_gclin	-0.041	0.076	0.590	-0.190	0.108
opvis_pclin	0.001	0.218	0.995	-0.425	0.428
cuc_mic					
ipadm_ghosp	-0.039	0.182	0.830	-0.396	0.318
ipadm_phosp	0.120	0.213	0.575	-0.298	0.538
opvis_ghosp	0.009	0.138	0.950	-0.262	0.279
opvis_phosp	-0.012	0.198	0.951	-0.400	0.376
opvis_gclin	-0.005	0.055	0.924	-0.112	0.102
opvis_pclin	0.008	0.017	0.616	-0.024	0.041
cus					
ipadm_ghosp	-0.009	0.120	0.939	-0.244	0.225
ipadm_phosp	0.108	0.102	0.290	-0.091	0.308
opvis_ghosp	0.056	0.080	0.488	-0.101	0.213
opvis_phosp	0.310	0.023	0.000	0.265	0.356
opvis_gclin	-0.016	0.081	0.843	-0.175	0.143
opvis_pclin	0.150	0.027	0.000	0.097	0.204
fpc					
ipadm_ghosp	0.159	0.082	0.057	-0.002	0.321
ipadm_phosp	-0.115	0.251	0.649	-0.607	0.378
opvis_ghosp	0.047	0.019	0.016	0.010	0.085
opvis_phosp	0.471	0.255	0.070	-0.030	0.972
opvis_gclin	0.041	0.059	0.488	-0.074	0.156
opvis_pclin	0.362	0.116	0.003	0.134	0.590

Note: Sample includes 26 countries with CIs for all 6 subsectors for all 4 methods

Table A4: Mean GHE CI estimates by subsector

	CI	se	pval	ci95_lo	ci95_up
ipadm_ghosp	0.003	0.017	0.862	-0.031	0.037
ipadm_phosp	0.110	0.054	0.045	0.003	0.217
opvis_ghosp	0.006	0.024	0.799	-0.041	0.054
opvis_phosp	0.168	0.061	0.006	0.049	0.287
opvis_gclin	-0.022	0.018	0.211	-0.057	0.013
opvis_pclin	0.096	0.031	0.002	0.034	0.158

Note: CUS method. Sample includes 69 countries with CIs for all 6 subsectors

Table A5: Mean GHE CI estimates by subtotal

	CI	se	pval	ci95_lo	ci95_up
IP	0.021	0.016	0.177	-0.009	0.052
OP	0.037	0.015	0.016	0.007	0.067
PUBL	0.006	0.014	0.660	-0.021	0.034
PRIV	0.119	0.038	0.002	0.045	0.193
TOTAL	0.032	0.013	0.012	0.007	0.057

Note: CUS method. Subsector concentration indices weighted by NHA shares where available; micro shares used otherwise. Sample includes 66 countries with CIs for all 4 subtotals and total

Table A6: Differences between means of WHS and non-WHS countries on correlates of GHE concentration index

	All countries with data on variable					Countries with data on all variables				
	N	WHS	Other	t	p>t	N	WHS	Other	t	p>t
Log GDP per capita	198	8.064	7.557	0.75	0.457	165	8.093	7.877	2.09	0.038
Log GHE per capita	185	4.660	3.972	1.53	0.127	165	4.660	4.188	2.15	0.033
GHE as % GDP	187	3.826	3.155	0.48	0.634	165	3.879	3.645	2.43	0.016
GHE as % THE	187	55.428	53.909	-0.66	0.513	165	56.071	57.471	0.70	0.485
Voice	174	0.117	-0.263	2.75	0.007	165	0.172	-0.311	2.85	0.005
Political stability	174	-0.011	-0.176	1.31	0.192	165	0.029	-0.214	1.33	0.184
Government effectiveness	174	0.274	-0.218	3.53	0.001	165	0.315	-0.267	3.51	0.001
Regulatory quality	174	0.222	-0.216	3.22	0.002	165	0.289	-0.268	3.44	0.001
Rule of law	174	0.116	-0.251	2.63	0.009	165	0.168	-0.290	2.74	0.007
Control of corruption	174	0.182	-0.194	2.62	0.009	165	0.225	-0.229	2.67	0.008

Note: Data are from WDI and WGI. “Other” means non-WHS countries.