

Inequality in access to human resources for health: measurement issues

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Introduction

Inequality in the distribution of health workers (HWs) has been a persistent policy concern throughout the world (Gravelle & Sutton, 2001). Most frequently it has focused on the distribution of health workers within countries (Gupta et al., 2003; Gravelle & Sutton, 2001), but recently attention has also been directed to the distribution across countries (e.g. Chen et al., 2004). It has been argued, for example, that one of the main limitations that developing countries face in achieving an optimal level of coverage of key health interventions is the exodus of their HWs to more developed countries – something that reinforces the already unequal global distribution of HWs (Hagopian et al., 2004). Poor countries thus face the double challenge of educating HWs and implementing policies to keep them within the national borders.

To allow comparisons of the inequality of HW distributions across countries or over time, it is useful to have a single summary measure of the distribution. A large number of measures have been developed to describe the inequality of income distributions (Anand et al., 2001), but the study of inequalities in the distribution of HWs is less advanced. The Gini coefficient has been used most frequently (e.g. Brown, 1994; Gravelle & Sutton, 2001; Gupta et al., 2003), although Gravelle and Sutton (2001) also used the Atkinson index to summarize the distribution of general practitioners in England and Wales.

The reasons for the choice of these indicators were not always specified. Each of the possible inequality measures has its own characteristics and it is important to consider them before choosing the most appropriate indicator. Anand et al. (2001) proposed that four properties should be considered before such a choice is made:

1. **The population grouping across which inequality is to be assessed:** The value of most inequality measures changes if larger or smaller groupings of a population are chosen: inequalities are more accentuated when described across smaller geographical divisions (Anand et al., 2001). This problem is called the scale or areal aggregation problem in a spatial inequality study. In the context of HWs, the value of a given inequality measure can change depending on whether it is measured at national, state or city level.
2. **The reference group or norm against which differences are measured:** Inequality may be measured against a benchmark (i.e. an "optimal" number of HWs per inhabitant within a country, for example) or it could be measured compared to a mean (e.g. the standard deviation of logs or the Theil coefficient), or by comparing every pair of units (e.g. the Gini coefficient). The Gini coefficient, the Generalized Entropy and the Atkinson family of inequality measures assess relative inequality while the standard deviation, for example, is an absolute measure.
3. **The choice between absolute versus relative measures:** A family of measures assesses relative inequality: they are unaffected by doubling the number of HWs per capita in each geographical area, for example. But they do change if the absolute number of health workers per capita increases by the same amount in each area. A second family of indicators measures absolute inequality. Increasing the number of HWs per capita in each area by the same number, so that the absolute differences among areas are preserved, would have no effect on them, while doubling the number in each area would.
4. **The weights to be attached to various points along the distribution:** Different measures give more weight to changes in the upper tail (e.g. the Theil coefficient), the lower tail (e.g. the mean of the logarithm) or to the middle of a distribution (Gini). The Atkinson incorporates an "aversion to inequality" parameter, which captures a society's preference for changes in distribution along its length (Anand et al., 2001). Gakidou et al. (1999) introduced a similar concept (called "alpha") that could be used to differentially value changes at different points in the distribution. It might be argued that improvements in health practitioner inequality in the worst areas should be weighted more than improvements among the areas with more practitioners/capita.

In empirical studies, a fifth criterion could be added: inequality indices may have different sensitivity to data contamination (i.e. data with measurement errors). Thus, when data do not offer a "certainty" of being "reasonably" clean and when the "direction" of the biases involved is not known, it might be a good idea to choose inequality indices that are not very sensitive to contamination.

Table 1 classifies the most common inequality indicators according to the main categories outlined above. Formal definitions for each can be found in Anand et al. (2001) and Mackenbach & Kunst (1997).

Table 1. Characteristics of major summary measures of inequality for continuous variables

Inequality index	Reference group	Absolute versus relative measure	Weights attached
Gini coefficient	Inter-individual	Relative	Middle of the distribution
Standard deviation of the logs	Mean	Relative	Lower tail of the distribution
Theil index	Mean	Relative	Upper tail of the distribution
Atkinson index	Inter-individual	Relative	Depends on the value of the parameter of aversion to inequality
Decile ratio	Inter-group	Relative	Both tails of the distribution
Index of dissimilarity	Inter-group	Relative / Absolute	Both tails of the distribution
Variance	Mean	Absolute	Both tails of the distribution

An extension that might be relevant for measuring HW inequality would involve comparing the distribution of health workers with the distribution of GDP per capita or with the distribution of need in the population – perhaps measured in terms of burden of disease or mortality. The resulting graph is called a concentration curve and a summary measure, called the concentration index, can also be defined (Wagstaff et al., 1991). However, in this paper we simply consider the scale question, something that is critical for measures of health worker dispersion where geographical areas or population groupings must be used.

It is generally accepted that the indicators in Table 1 that describe the entire distribution are susceptible to the scale problem, which would make it meaningless to compare their values estimated for the distribution of HWs across countries, except in the special case where the sizes of the geographical areas being considered are roughly the same across countries. The same problem applies to considering changes in inequality over time in the same country: if population size increases or administrative boundaries are changed, the estimates of inequality are not comparable.

For this reason, we explore whether it is possible to select an indicator which is not very sensitive to the scale problem. The paper, therefore, first describes the scale problem with a simple example, then tests how sensitive a simple ratio measure of the distribution of health workers is to changes in scale. We illustrate this ratio first with the global distribution of health workers and then with the distributions within Brazil, Indonesia and Viet Nam.

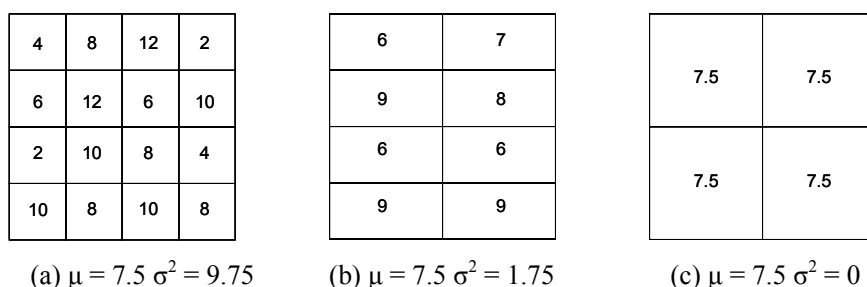
Materials and methods

The scale problem

Income inequality is generally measured across individuals, so the scale problem described above does not apply. Gini coefficients of income distribution can be compared across countries and over time, for example. However, this is not the case for inequalities in the dispersion of HWs, where geographical areas or population groupings must be used. The scale problem is illustrated in Figure 1 (adapted from Barber, 1988) showing the number of HWs per capita. We illustrated the problem with the variance, but it is also possible to show that the values of all of the summary indicators of the distribution of health workers as a whole in Table 1 are sensitive to the level of geographical or population aggregation used.

In (a) the areal distribution is shown in an area with 16 cells – let us call them municipalities. The mean value is $\mu = 7.5$ and the variance is $\sigma^2 = 9.75$. In (b), these data are aggregated into larger units, called districts, by joining neighbouring cells. The value in each cell is the average value of health workers per population derived by aggregating the data from Table 1a. This leads to the same mean value but to a smaller variance. Repeating this operation results in no variance at all (c).

Figure 1. Effects of areal aggregation



Three additional problems arise when virtually any summary statistic of the overall distribution is applied to spatial data (Barber, 1988), often described as the boundary problem, the problem of modifiable units and the problem of pattern. Combined with the space problem, they mean that any measure of these measures of inequality or dispersion cannot be interpreted independently from the study area and are generally incapable of assessing many patterns that can be observed on a map.

However, here we focus on the scale question and what inequality index should be used, given this problem. Because information on HW numbers is usually provided by administrative area within a country, and these areas vary considerably in population size, none of these indicators can be used to compare the inequality of HW distributions across settings. They could be used to compare distributions within a country over time, but only if the population size of administrative units did not change.

We therefore explore here if a simple ratio measure of inequality solves this problem. We consider two ways of estimating the proportion of the health workforce available to the top 10% of the population, compared to the bottom 10%, and test the extent to which the ratio is also sensitive to the level of aggregation, using the real data mentioned below.

Data

World

Data on the number of health workers in WHO Member States was updated and revised for the *World health report 2006*. Although it is the most up-to-date and complete data base available, information on only doctors, nurses and midwives is complete for all 192 countries, so those data are used in this paper.

Brazil

Data on HWs at municipal level were extracted from a representative sample of 11.7% of households in the *Census 2000*. This census identified 21 categories of HWs classified by the International Standard Classification of Occupations (ISCO) 4-digit codes for the health industry. Population per municipality was also taken from the census. There are 5507 municipalities and 27 states in Brazil.

Indonesia

In this case, data on HWs were obtained from the Ministry of Health (MOH) Inventory for 2001, in which data are recorded for public and private hospitals and public health centres. Independent private practitioners are not included in this dataset. Human resources data were not available for around 8% of all hospitals (accounting for 3% of beds) and for 12% of all health centres. The MOH (Indonesia) coding system was used to classify the health workers. Population data were obtained from the 2000 census. Health worker numbers were extracted from the MOH inventory (2001) for 29 provinces and 327 districts, each of which is an independently administered subnational unit. A province is the first subnational level, whereas districts are the second-level units.

Viet Nam

Health worker numbers were taken from the 3% sample of the 1999 *Population and housing census* (Viet Nam, 1999). HWs were taken to be the respondents who selected the "health activities" industry code (851). They included health professionals (except nursing) – mostly doctors – nursing and midwifery professionals and a group classified as associate professionals. Sample weights were used to obtain national estimates for all categories. Population data were also obtained from the census. Subnational data for numbers of HWs were extracted for eight economic regions and 61 provinces from the census. Each province is an independently administered unit in Viet Nam.

A ratio to express inequality

As shown above, comparing inequality measures across countries is problematic when the sizes of administrative units differ from one country to another. One way to reduce this problem could be to compare groups across countries which do not coincide with administrative areas. That can be achieved by comparing the availability of health workers to people at the top and at the bottom of the distribution. The decile ratio is one such indicator.

There are two ways of calculating this ratio for HWs. In both, it is necessary to order the population by availability of HWs per capita. In the first, the HWs per capita for the population at the 10th and the 90th percentile are calculated. For example, if the number of HWs per 1000 population separating percentile 10 from the 11th percentile is 2, and the number of doctors per 1000 population separating the 89th from 90th percentile is 15, the ratio will be equal to 7.5. The main advantage of using this ratio is that it is relatively robust to the existence of outliers (at the top or at the bottom of the distribution), while the main disadvantage is that it directly uses only two points of the entire distribution.

The second way of calculating the ratio is based on the Lorenz curve (using the so-called Kuznets ratios). The share of total health workers available to different population groupings is ordered, from lowest to highest, as in Table 2.

Table 2. Work table for HW decile ratio calculations

State	Population	HWs per 1000 population	Share of the total HWs
A	2000	2	7.9%
B	3000	3	17.6%
C	1000	4	7.9%
D	2000	7	27.4%
E	2000	10	39.2%
Total	10000	5.1	100%

If we assume that the two doctors per 1000 is spread equally over the population in state A, the bottom 10% of the population has access to 3.95% (7.9/2) of health workers. Similarly, the top 10% has access to 19.6% (39.2/2) of health workers. This "decile ratio" therefore equals 4.96.

Obviously, this averaging of the population at the first and last quintile involves a loss of precision; working with deciles would be preferable. The impact of the scale problem on the decile ratio is illustrated in the results section.

Results

The two decile ratios are calculated in Table.3. The first row summarizes the global distribution of health workers, by means of two geographical groupings – the six WHO regions and the 192 WHO Member States. We then report the ratios, using two geographical groupings for Brazil, Viet Nam and Indonesia.

Table 3. Two inequality indicators for the distribution of health workers across the world and within Brazil, Viet Nam and Indonesia.

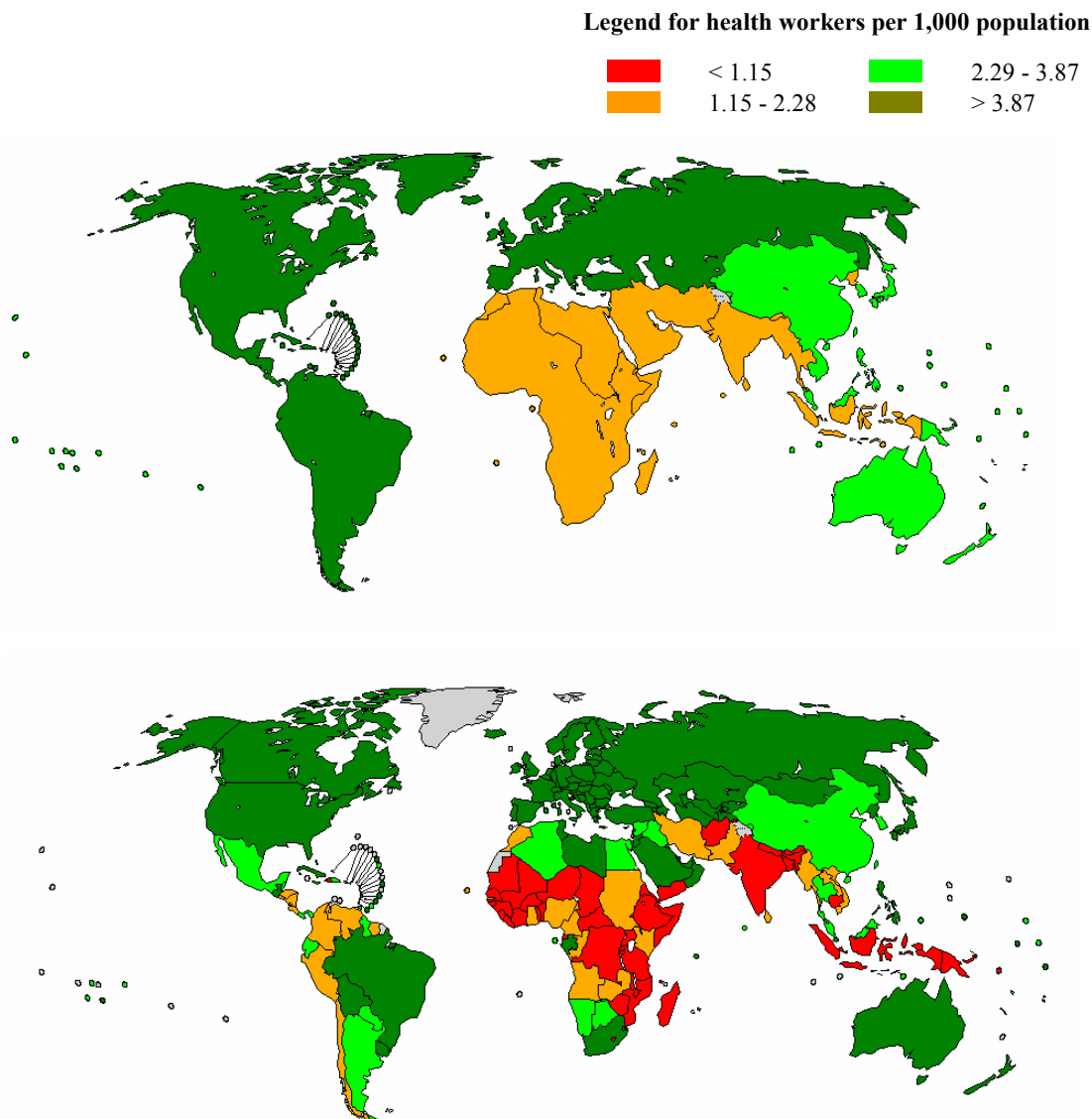
Countries	Units used	Ratio of min (p90)/max (p10)	Ratio of proportions (p90/p10)
Global for the world ¹	WHO-regions (6)	9.6333	9.6333
	192 countries	18.2558	26.1297
Brazil ²	States (27)	1.4246	1.8344
	Municipalities (5507)	4.1903	7.2715
Indonesia ⁴	Provinces (29)	2.4685	3.5541
	Districts (327)	6.7283	20.3496
Viet Nam ³	States (8)	2.2122	2.2122
	Districts (61)	6.3212	9.6957

Sources: ¹WHO Global Database 2006 (192 countries), ²Brazil Population Census 2001, ³Viet Nam Population and Housing Census 1999, ⁴Indonesia Ministry of Health Inventory 2001

It is clear that the value of the decile ratio also depends on the size of the geographical unit chosen. The smaller the size of the unit, the greater is the apparent inequality in distribution. This is because it is not possible to identify health worker availability per individual. (In fact, health worker density defined at the individual or small-group level does not have a clear meaning, something discussed subsequently.) Population groups must be used to estimate the decile ratio, and the larger the population group, the less accurate is the estimate of availability at the 10th and 90th percentiles. This means that it is not possible to compare the estimated decile ratio across countries because the sizes of the administrative units differ.

The space effect is easy to illustrate graphically. Figure 2 shows the distribution of HP across the world at the regional (a) and national (b) level (WHO, 2006). Access to health workers is uneven across the world. The greatest burden of disease is in AFR, yet it has access to proportionally fewer health workers and proportionally less of the global health expenditure. We also see that the regional grouping of countries shows far less inequality than using national boundaries.

Figure 2. Global distribution of the stock of health workers (per 1000 inhabitants) at the regional (a) and national (b) level (WHO, 2006)



Similar patterns can be observed in countries; we illustrate only for Viet Nam and Brazil here (the legend used is the same as that for Figure 2).

Figure 3 shows that in Brazil every state has access to more than 3.87 health workers per 1000 population on average (in part (a) for states), though inequalities across municipalities are very clear and nearly 25% of all municipalities have access to fewer than 2.29 health workers per 1000 population (part (b) for municipalities).

Figure 3. Distribution by states (a) and municipalities (b) of the stock of health workers in Brazil (per 1000 inhabitants). Source: *Brazil population census 2001*.

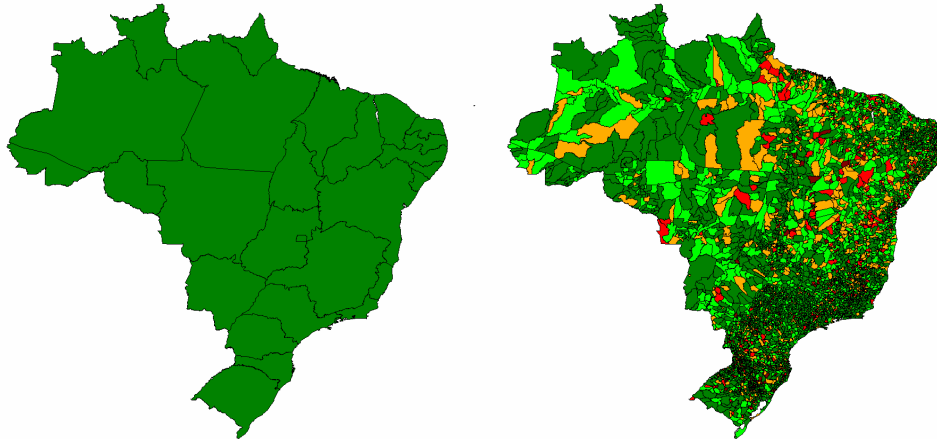
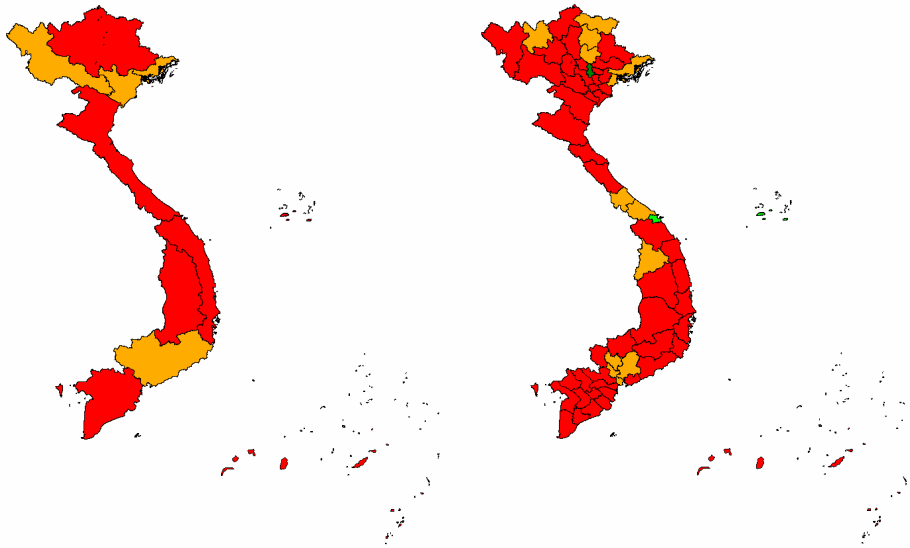


Figure 4 shows that all eight regions and 59 of the 61 provinces in Viet Nam on average have access to fewer than 2.29 health workers per 1000 population; part (a) using a breakdown by region, and part (b) using a province breakdown. The smaller the unit, the more accurate the information on shortages.

Figure 4. Distribution by regions (a) and provinces (b) of the health workers in Viet Nam (per 1000 inhabitants). Source: Viet Nam population and housing census 1999.



Discussion

There have been a number of previous attempts to summarize inequalities in the distribution of HWs using a single number, in line with the literature comparing inequality in income across countries or subnational units. We have argued that all summaries of the distribution as a whole, such as the variance, the Gini coefficient and the Atkinson index suffer from the problem of space and their values cannot be compared across settings. This limits the usefulness of earlier studies (e.g. Gupta et al., 2003).

We tested in this paper whether a simpler indicator that does not describe the entire distribution – the decile ratio – is subject to the same problem. And it seems to be, because individuals at the 10th and 90th deciles must be assigned the average health worker density for the population group to which they belong. Such averaging results in an underestimate of inequality. Accordingly, the decile ratio cannot be compared across countries either, and can be compared over time in the same country only if there is no change in the size of administrative units. Population growth, migration and changes in administrative boundaries mean that this is unlikely to be the case for very long.

The question then, is whether any single summary indicator of inequality in the distribution of health workers that is not sensitive to the space problem can be defined. Within countries it would be possible to estimate the number of administrative units with lower than the desired density of health workers – similar to the information presented in Figures 3 and 4 – Viet Nam and Brazil. This is useful for policy purposes but cannot be used for comparative purposes across countries.

We believe that the space problem is likely to be avoided only with indicators that take the individual or household as the unit of analysis. As we implied earlier, this rules out using health worker density as the quantity of interest. The density for a household is meaningless. Even the density for a small group of people has no practical meaning. For example, a number of municipalities in Brazil have no doctors, nurses or midwives, but this does not mean they have no access to health workers or services. Cross-border flows assure service availability.

The appropriate concept might be whether the individual could use the services of a health worker in a reasonable time if needed. This would require considerably more work to operationalize, partly because it would be necessary to determine the time limit for obtaining services; many factors

determine whether people can use services, including the distance from health facilities, the nature of the terrain and the costs of transport and care.

We are exploring whether recent mapping tools such as AccessMod© can provide at least a partial solution. This tool in particular could not cover the question of affordability, but it could help to identify the proportion of the population who could reach a health facility within a specified period of time. This work continues.

References

- Anand S, Diderichsen F, Evans T, Shkolnikov VM, Wirth M (2001). Measuring disparities in health: methods and indicators. In: Evans T, Whitehead M, Diderichsen F, Bhuiya A, Wirth M, eds. *Challenging inequalities in health: from ethics to action*. New York, Oxford University Press:49–67.
- Barber G (1988). *Elementary statistics for geographers*. New York, The Guilford Press.
- Brown MC (1994). Using Gini-style indices to evaluate the spatial patterns of health practitioners: Theoretical considerations and an application based on Alberta data. *Social Science Medicine* 38(9):1243–1256.
- Chen L, Evans T, Anand S, Boufford JI, Brown H, Chowdhury M, Cueto M, Dare L, Dussault G, Elzinga G, Fee E, Habte D, Hanvoravongchai P, Jacobs M, Kurowski C, Michael S, Pablos-Mendez A, Sewankambo N, Solimano G, Stilwell B, de Waal A, Wibulpolprasert S (2004). Human resources for health: overcoming the crisis. *Lancet*, 364:1984–1990.
- Gakidou EE, Murray CJL, Frenk J. *A framework for measuring health inequality*. Global Programme on Evidence for Health Policy Discussion Paper Series: No. 5. Geneva, World Health Organization.
- Gravelle H, Sutton M (2001). Inequality in the geographical distribution of GPs in England and Wales 1974-1995. *Journal of Health Services Research and Policy*, 6:6–13.
- Gupta N, Zurn P, Diallo K, Dal Poz MR (2003). Uses of population census data for monitoring geographical imbalance in the health workforce: snapshots from three developing countries. *International Journal for Equity in Health*, 2:11.
- Hagopian A, Thompson M, Fordyce M, Johnson K, Hart LG (2004). The migration of physicians from sub-Saharan Africa to the United States of America: measures of the African brain drain. *Human Resources for Health*, 2:17.