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Inequality decomposition and geographic targeting with applications to China and Vietnam

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Summary

How far are income-related inequalities in the health sector due to gaps *between* poor and less poor areas, rather than due to differences between poor and less poor people *within* areas? This note sets out a method for answering this question, and illustrates it with two empirical examples. The disproportionate accrual of health subsidies to Vietnam's better-off is found to be largely due to the fact that richer provinces have larger per capita subsidies, while pro-rich inequalities in health insurance coverage in rural China are found to be largely due to the fact that better-off villages have been more successful at preventing the collapse of their insurance schemes. Copyright © 2005 John Wiley & Sons, Ltd.

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Introduction

Geographic targeting is a potentially attractive policy instrument for narrowing income-related inequalities in the health sector. Many countries use geographic resource-allocation formulae to allocate government subsidies. Many designate certain areas 'deprived' and grant inhabitants of these areas certain cash and in-kind benefits, including sometimes health cards if not formal health insurance coverage. (Vietnam is an example [1].) Many contingent cash transfer programs in Latin America [2] employ geographic targeting, as do bilateral and multilateral donors in their aid programs in the health sector. The scope for geographic targeting is increasing rapidly with the development of poverty mapping techniques that allow small-area poverty and inequality statistics (and their standard errors) to be computed by combining household survey and census data [3]. The use of geographic targeting to address income-related health sector inequalities raises an obvious question: How far are income-related inequalities due to gaps between poor and less poor *areas*, rather than due to differences between poor and less poor people *within areas*? This note sets out a method for answering this question, and illustrates it with two empirical examples.

A geographic decomposition of the concentration index

Our interest is in understanding the role of geographic differences in contributing to income-related inequalities in the health sector. These inequalities can be measured using the concentration index, equal to twice the area between the line of equality and the concentration curve, $L(s)$,

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formed by plotting the cumulative share of the health sector variable in question – call it y – against the cumulative population or sample share, where people have been ranked by their income, beginning with the poorest [4,5]. Negative values of the index indicate that y is higher, on average, among the poor, while positive values indicate concentration among the better off. The larger the index is in the absolute size, the greater the degree of inequality, with -1 and $+1$ being the bounds.

By analogy with the geographic decomposition of the closely related Gini coefficient [6], and in a similar way to [7], we can write

$$C = C_B + \sum_i \alpha_i C_i + R \tag{1}$$

where C is the concentration index calculated on the full sample, C_B is the between-areas concentration index described below, there are $i = 1, \ldots, N$ geographic areas, α_i is the product of the ith area's population share and its share of y, C_i is the concentration index of the ith area, and R is a reranking term described below.[a,b]

C_B is computed by assigning all individuals in a given area the mean value of y in that area, lining up areas by their mean per capita income, and computing the corresponding concentration index for y. It corresponds to a move from the line of equality to the concentration curve corresponding to the above calculation, $L_B(s)$. C_B thus captures the extent to which poor areas systematically have smaller or larger values of y than better-off areas.

C_i indicates the extent of income-related inequality in y in area i. The weighted sum of these N concentration indices captures the fact that *within areas* the poor systematically have smaller or larger values of y. This corresponds to the movement from $L_B(s)$ to the concentration curve formed by keeping the N areas arranged in ascending order of mean income but allowing for within-area variation in y. This second concentration curve, $L_W(s)$, will lie further from the line of equality than $L_B(s)$.

This leaves R, which is computed as a residual. This corresponds to the move from $L_W(s)$ to $L(s)$, the concentration curve corresponding to C. The income ranges are likely to overlap, so that, for example, the richest person in area 1 is likely to be richer than the poorest person in area 2, and so on. Except in the case that everyone's health is the same, this will mean that $L_W(s)$ will not overlap with $L(s)$. If richer people typically have higher values of y, their shuffling up the income distribution – as they overtake poorer people in richer regions who were previously ranked farther up the distribution – will make $L(s)$ lie further from the line of equality than $L_W(s)$. We would thus expect R to be positive in the case where y is a 'good' and a 'normal' one at that. Its magnitude depends on *both* the extent of reranking in the move from $L_W(s)$ to $L(s)$ *and* the size of the covariance between income and y. It is therefore a mixture of within- and between-area income-related inequality in y.

Illustration I: government subsidies to the health sector in Vietnam

In 1998, 14% of health spending in Vietnam was financed out of taxes, with the provinces accounting for 11 of these 14 percentage points [8]. Donors and social health insurance each accounted for around 2%, with the remaining 81% being paid out-of-pocket by households. Somewhat surprisingly – given Vietnam's recent history – government subsidies from all levels of government combined disproportionately benefit the better-off [9]. Furthermore, per capita subsidies to the health sector in Vietnam are larger in richer provinces than in poorer provinces [1]. The latter is due in part to the fact that provinces themselves raise a substantial – and increasing – share of their health budgets from their own revenues, and that richer provinces have a larger tax base. Equation (1) can be used to assess the extent to which the higher incidence of subsidies among better-off *people* is due to richer *provinces* providing larger subsidies per capita rather than to subsidies disproportionately benefiting the better off within provinces.

The latest benefit–incidence analysis (BIA) study for Vietnam's health sector was based on 1998 utilization patterns in the hospital sector (outpatient and inpatient separately), commune health stations (CHSs) and polyclinics. Full details, obtained using data on 26 000 individuals from the 1998 Vietnam Living Standards Survey (VLSS), are reported elsewhere [10]. Using the same household-level and unit subsidy data, it is possible to disaggregate across 58 of Vietnam's 61 provinces (the VLSS was not fielded in all 61 provinces), and thereby decompose the concentration index for subsidies overall, as well as for sector-specific subsidies (inpatient, outpatient, etc.). The results for overall subsidies are shown in column 1 of Table 1.[c] The results suggest that C owes relatively little to 'pure' inter-province inequalities and is largely due to a combination (in roughly equal measure) of within-province inequalities and inequality attributable to the overlapping of the provinces' income ranges.

Column 2 paints an altogether different picture. Here, in contrast to the analysis in [10], allowance has been made for provincial variation in unit costs. The government does not report cost data by facility type by province, but data are available for 2000 on (all) government health spending for each province. The 1998 VLSS can be used to obtain provincial mean utilization rates in the absence of an alternative source. If we assume the *relative* unit costs for the various sub-sectors are the same across all provinces, and all provinces experienced the same growth of government health spending over the period 1998–2000, we can estimate province-specific unit costs for 1998. Unsurprisingly, these tend to be higher in richer provinces. And, unsurprisingly too, this changes the overall level of subsidy inequality (C rises by 60%), as well as the shares of the various components of the decomposition in Equation (1). C_B rises considerably, indicating that once allowance has been made for provincial differences in unit expenditures, much of the explanation for the poor 'capturing' a smaller share of the overall health subsidy in Vietnam is indeed the fact that poorer provinces have smaller amounts of money per capita going from tax revenues into their health budgets.

Column 2 may well overstate the contribution that provincial inequalities make to subsidy inequality in Vietnam. Provinces like Ha Noi and Ho Chi Minh have many national and regional centers of excellences to which patients from other provinces go and get treated. In the household data, these treatment episodes will be allocated to the province of residence, which will tend to bias upwards the unit cost estimate of provinces delivering 'cross-border' care, since facilities in these provinces will look less busy than they really are. Column 3 eliminates Ho Chi Minh from the exercise – the rich province where the discrepancy between the population and subsidy share is greatest.[d] As expected, overall inequality in subsidy incidence goes down, but so too does C_B – dramatically so. R rises substantially in value, reflecting presumably the fact that the remaining provinces are more homogenous in terms of income range than the country is as a whole.

Illustration 2: insurance coverage in rural China

It is known that health insurance coverage in China dropped during the 1970s and 1980s, that coverage of the rural cooperative medical scheme (CMS) has reached very low levels, and that the higher income groups are more likely to have health insurance in general than the poorer income groups [11,12]. Two things that are not apparently known are: how CMS coverage is distributed across income groups; and how far any income-related inequalities in CMS coverage are due to poorer villages being more likely to have lost their CMS (due, presumably, to their more limited communal funds to keep it going) rather than to the better-off within villages with a CMS being more likely to be enrolled.

Table 1. Decomposing subsidy incidence in Vietnam

Component of C	Values of C and its components		
	1 Calculated using national unit costs	2 Calculated using province-specific unit costs	3 As column 2 but excluding Ho Chi Minh City
C	0.1606	0.2547	0.1657
C_B	0.0061	0.1727	0.0089
$\sum \alpha_i C_i$	0.0718	0.0196	0.0130
R	0.0827	0.0623	0.1438

The value of $\sum \alpha_i C_i$ differs between columns 1 and 2 because although the individual C_i are the same, the α_i differ.

Table 2. Decomposing inequality in insurance enrolment, sample counties in rural China

Component of C	Value
C	0.2481
C_B	0.2244
$\sum \alpha_i C_i$	−0.0012
R	0.0250

Table 2 is based on an analysis of a baseline household survey undertaken as part of the World Bank's Health VIII project in China. The survey, which was conducted in 1998, covers 52 000 individuals from 13 000 rural households living in 225 villages in 22 counties in 12 poor provinces. It records *inter alia* household income over the last 12 months, and details of insurance coverage. The value of C of 0.2481 in Table 2 indicates that CMS coverage is indeed somewhat concentrated among the better-off. The decomposition in Equation (1) is performed at the village level – the unit of the CMS prior to the current reform initiative under which CMS will be developed at county level. The decomposition provides a clear answer to the question posed at the outset, at least for the counties in this sample: the lower CMS coverage among the poor is almost entirely due to poor villages having been more likely to have lost their CMS than to poor people within CMS villages being less likely to enrol. Apparently, in the relatively few villages (6 out of the 225 in the sample counties) where CMS still has members, membership is either very high (which guarantees low inequality), or membership does not vary systematically with income.

Conclusions

While the R term in Equation (1) can be interpreted in terms of an area between concentration curves, it is nonetheless unfortunate that C cannot be neatly decomposed into a within- and between-area component. However, in contrast to the case where one is measuring income inequality or pure health inequality, where neatly decomposable inequality indices such as the Theil index are available, this lack of neatness is inevitable given that our interest lies in the degree inequality in one variable (the health sector variable, y) across the distribution of another variable (income). Given this, Equation (1) provides a useful means of assessing how far income-related inequalities in a health sector variable are due to inequalities *between* poor and less poor areas rather than inequalities between rich and poor *within* areas.[e] Many applications other than the two presented here are clearly possible.

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Notes

a. Some of the C_i could be positive and some negative, such that $\sum C_i$ could be zero or close to it. In a full analysis, it could be interesting to report all the C_i, and not just their sum.
b. Standard errors for C_B and the C_i could be computed using the methods set out in [5], but are not computed in the illustrations that follow.
c. The results here are based on the first of the methods used in [10].
d. Excluding Ha Noi makes much less difference.
e. We could always talk in terms of bounds – for example, $C_B + R$ is, in effect, the upper bound on the between-area source of inequality.

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