Social Science & Medicine 88 (2013) 98–107

Contents lists available at SciVerse ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Is wealthier always healthier in poor countries? The health implications of income, inequality, poverty, and literacy in India

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ARTICLE INFO

Article history:
Available online 15 April 2013

Keywords:
India
Public health
Social well-being
Income inequality
Poverty
Literacy

ABSTRACT

Standard policy prescriptions for improving public health in less developed countries (LDCs) prioritise raising average income levels over redistributive policies since it is widely accepted that 'wealthier is healthier'. It is argued that income inequality becomes a significant predictor of public health only after the 'epidemiological transition'. This paper tests this theory in India, where rising income levels have not been matched by improvements in public health. We use state-, district-, and individual-level data to investigate the relationship between infant and under-five mortality, and average income, poverty, income inequality, and literacy. Our analysis shows that at both state- and district-level public health is negatively associated with average income and positively associated with poverty. But, at both levels, controlling for poverty and literacy renders average income statistically insignificant. At state-level, only literacy remains a significant and negative predictor. At the less aggregated district-level, both poverty and literacy predict public health but literacy has a stronger effect than poverty. Inequality does not predict public health at state- or district-levels. At the individual-level, however, it is a strong predictor of self-reported ailment, even after we control for district average income, individual income, and individual education. Our analysis suggests that wealthier is indeed healthier in India – but only to the extent that high average incomes reflect low poverty and high literacy. Furthermore, inequality has a strong effect on self-reported health. Standard policy prescriptions, then, need revision: first, alleviating poverty may be more effective than raising average income levels; second, non-income goods like literacy may make an important contribution to public health; and third, policy should be based on a broader understanding of societal well-being and the factors that promote it.

Introduction

A large body of research has linked higher average income levels in less developed countries (LDCs) to improved public health through materialist mechanisms (Preston, 1975; Pritchett & Summers, 1996). Other factors that affect social well-being such as inequality, especially through non-materialist pathways, are assumed to be insignificant in LDCs. The policy prescription is simple: social well-being in poor countries is best improved by increasing GDP per capita (Anand & Ravallion, 1993; Dollar & Kraay, 2002). This paper uses state-, district-, and individual-level data to test the associations between public health and average income, poverty, income inequality, and literacy in India. It demonstrates that this simple policy prescription must be qualified.

The policy debate arises between three main positions: pro-market liberalizers, the psycho-social school, and a pro-poor position. Pro-market liberalizers – who are dominant in the policy debate – argue that raising average incomes through economic liberalization is the most effective way to improve public health. They point to seminal work by Preston (1975) and Pritchett and Summers (1996) that shows the relationship between average income and health is curvilinear and concave, and that the causal direction is from wealth to health. Their argument is based on reducing material deprivation: higher average incomes allow public investment in health infrastructure at the societal-level and sufficient expenditure on diet and medicine at the individual-level to protect health (see also Anand & Ravallion, 1993; Dollar & Kraay, 2002).

The psycho-social school, focussing on developed countries, accepts these materialist pathways and the important role of average income levels but also introduces non-materialist

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http://dx.doi.org/10.1016/j.socscimed.2013.04.004

pathways and income inequality. For individuals with relatively low incomes, inequality generates stress that damages health directly through 'psycho-neuro-endocrine' mechanisms and indirectly through unhealthy behaviours associated with stress, like smoking and alcohol abuse. Socially, these feelings manifest as reduced civic participation and anti-social behaviour, affecting the health of others, including those higher up the income range (Lynch, Smith, Kaplan, & House, 2000:1201; Marmot, 2002; Murali & Oyebode, 2004; Wilkinson, 1996, 1997). This view is closely related to the 'social capital' paradigm, in which inequality reduces 'civic engagement' and 'levels of mutual trust' (Kawachi & Kennedy, 1999; Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997:1492). In this paradigm it is this fraying of social bonds that gives rise to both the individual and social effects that, in turn, manifest as poorer public health. These effects are often captured in objective measures of public health like infant or under-five mortality or life expectancy. But more subjective measures of well-being such as 'life satisfaction' and self-reported health have received increasing attention following work by Stiglitz, Sen, and Fitoussi (2008) advocating more holistic measures of development, including public health.

Wilkinson (1994) locates materialist and non-materialist pathways on either side of the inflection point in the Preston curve – the 'epidemiological transition' (Fig. 1). Before this transition, the leading cause of mortality is material deprivation; after it the effects of inequality predominate. Frey and Stutzer (2002) and Inglehart (2002) make analogous policy prescriptions for subjective measures like life satisfaction: poor countries must prioritise raising average incomes; only policy in rich countries can afford to be broader.

The pro-poor position extends the psycho-social school's paradigm beyond developed countries and posits that both materialist and non-materialist mechanisms operate in LDCs too. It shows that the effects of economic growth are strongly mediated by inequality

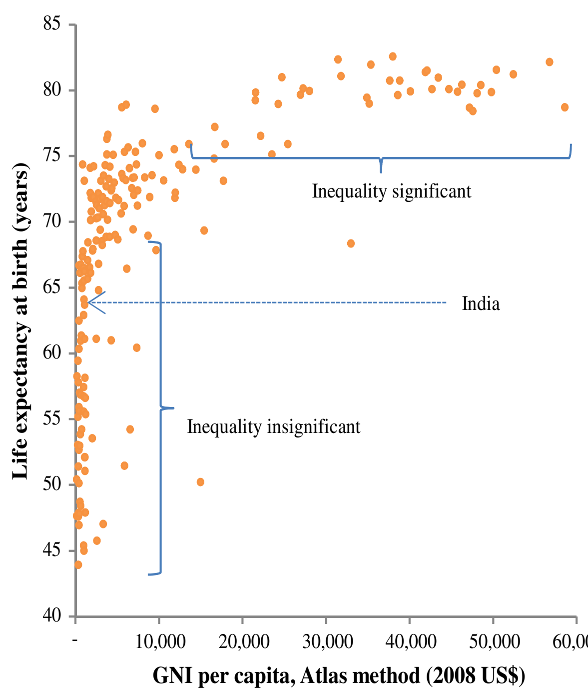

Fig. 1. The Preston curve and the epidemiological shift.[ab] Source: World Development Bank Indicators. [a]In 2008 the average life expectancy in India was 64 years and gross national income per capita US$1080. [b]The curve would be more linear if in purchasing price parity (PPP) terms. But it would still slope upwards: PPP would attenuate but not completely undermine either societal- or individual-level operators.

and poverty. Biggs, King, Basu, and Stuckler's (2010) study of 22 Latin America countries over 47 years suggests that although average income is the key determinant of public health, its positive effects are almost absent when growth is accompanied by rising inequality and poverty. Here one effect of inequality may be political: "the greater the income gap, the greater the disparity in interests. This translates, because of the clout of the elite, into constant pressure for lower taxes and reduced public spending [on public health]" (Krugman, cited in Kawachi & Kennedy, 1999:221). (Bertola (1993) and Perotti (1993) have constructed models that connect income inequality to support for a tax to fund a public good such as public healthcare.) The pro-poor position echoes the 'Easterlin paradox', which juxtaposes substantial increases in per capita incomes with paltry rises or even falls in subjective measures of well-being, especially in transitional economies. Materialist variables like average income and poverty may be the chief determinants of objective measures of public health like infant mortality rates but this work suggests that even in developing countries inequality, among other factors, undermines more subjective measures, including life satisfaction and self-reported health, and thereby undercuts the gains made by increasing income levels (Brockmann, Delhey, Welzel, & Yuan, 2009; Easterlin, 2010, 2003; Easterlin, Morgan, Switek, & Wang, 2012; Knight & Gunatilaka, 2011).

In summary, these theories implicate three main income-variables: average income, poverty, and income inequality; and four causal mechanisms: investment in infrastructure; personal protection of health; individual stress; and social capital. Investment in infrastructure and personal protection of health are materialist, whereas individual stress and social capital are non-materialist. By level of operation, however, investment in infrastructure and social capital are at societal-level whereas personal protection of health and individual stress are at individual-level (Fig. 2). (In reality these mechanisms are interdependent and not easily isolated – see Pickett & Wilkinson, 2009, on 'compositional' and 'contextual' factors.)

Although this study's central aim is to compare the effects of average income levels with those of income distribution on public health, the analysis below also introduces literacy rate as an alternative predictor to income-measures. The predictive power of literacy has been well-established in both developed and developing countries and can be located in both materialist and non-materialist mechanisms (see literature surveys in DeWalt, Berkman, Sheridan, Lohr, & Pignone, 2004; Kabir, 2008:186187; WHO, 2007). Literacy mediates the investment in infrastructure pathway by enabling a population to engage with the healthcare infrastructure available and respond to public health campaigns (DeWalt et al., 2004:1232). In poor countries female illiteracy in particular is associated with child mortality (Caldwell, 1986:184–187; Sen, 1999:195–198). At the individual-level it is associated with better personal protection of health, including healthier behaviours such as not smoking and improved diets (Kabir, 2008:186). And, to the extent that it is a marker of an individual's socio-economic status, it may also be implicated in the non-materialist individual stress pathway (DeWalt et al., 2004:1237).

Case selection

We focus on India, home to over one sixth of the world's population and one third of the world's poor, in which the effects of liberalizing reforms since the mid-1980s are hotly contested. The World Bank (undated) estimates 37% of India's population live on less than US$1.25 per day. Oxford University's Multidimensional Poverty Index (2010) gives an even higher figure of 55% – over 600 million people. Several analysts have noted that India's public health indicators have failed to keep pace with its GDP (Horton &

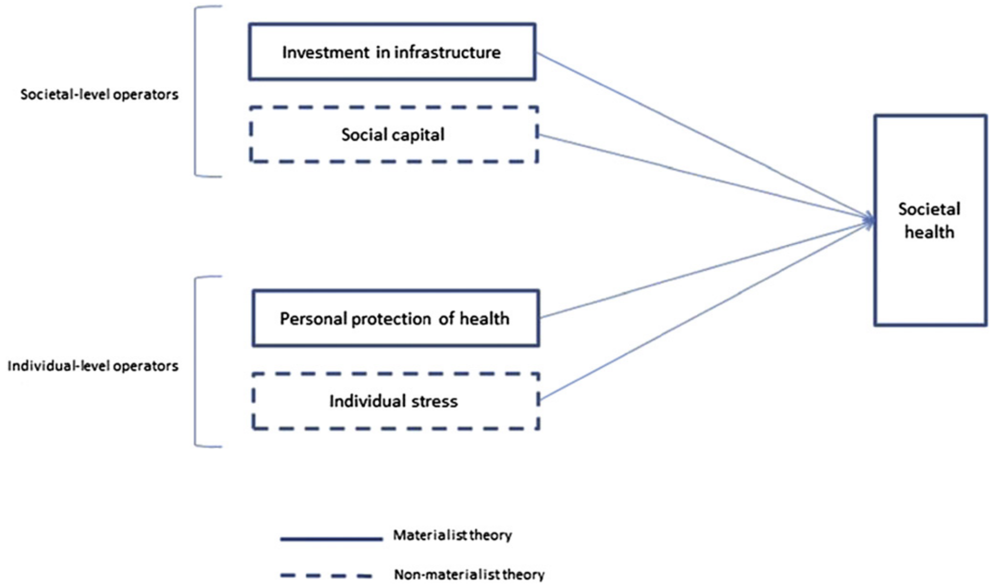

Fig. 2. Pathways to public health – levels of operation and theoretical bases.

Das, 2011; Subramanyam, Kawachi, Berkman, & Subramanian, 2010). World Bank (2013) indicators show life expectancy at birth in China is 73 compared with 65 in India and infant mortality rate per 1000 live births is 13 compared with 47 (2011 data). At the extreme, these failures have galvanized anti-state movements including the Maoist insurgents or Naxalites (Kennedy & King, 2011). Others have noted that India's health crisis tends to be explained in terms of access to healthcare (Narayan, 2011). While this is clearly a very important factor, these accounts tend to neglect socio-economic factors such as poverty and inequality, which have proven to be powerful determinants of public health in Western Europe.

Analyses of the role of inequality in public health tend to bypass the poorest countries (exceptions include Biggs et al., 2010; Ram, 2006). In a meta-analysis of literature in the area, however, Subramanian and Kawachi (2004) note more studies of poor societies are needed – and at a sub-national level. This study, then, supplements the existing literature in two main ways. First, it focuses on a poor country. In per capita terms, India is considerably poorer than China or the Eastern European transition economies that are at the heart of studies of the 'Easterlin paradox'. Second, it complements those framed at country-level (Biggs et al., 2010, on 22 Latin American countries; Ram, 2006, on a broader sample of countries) or state-level (Kawachi et al., 1997, studying 39 US states; James & Syamala, 2010, studying 15 Indian states) by testing the relationship between inequality and public health at the lower level of the Indian district, the almost 600 administrative units below Indian states. As well as providing ample statistical power, framing analysis at district-level may also render non-materialist pathways more plausible, since district-level inequality is likely to be more immediate to the individual than national- or state-level inequality. And since the Indian district is an administrative unit, some political mechanisms may also be implied in our results.

Methodology and hypotheses

Data

Data for state-level analysis are drawn from various official sources – see Appendix A. For district- and individual-level analyses we use two sources: the 2001 Indian census and the 60th survey round of the Indian National Statistical Survey Office (NSSO), conducted in 2004. Under-five and infant mortality rates for 479 districts across 17 major states, accounting for roughly 95% of India's total population, have been calculated by Rajan, Nair, Sheela, Jagatdeb, and Mishra (2008) using the 2001 census. These are used alongside self-reported ailment by individuals and district-wise measures of average income, poverty gap, income inequality, and literacy based on data from the NSSO's 60th survey round on healthcare and morbidity conducted between January and June 2004. The round surveyed 383,346 individuals across 583 districts in all 35 states and Union Territories (a small number of remote areas were not surveyed – see NSSO, 2006:2). NSSO provide stratus weights that allow aggregate district-level and state-level population estimates from survey data. These weights, reflecting NSSO's stratified sample selection process and relating the estimated proportion an individual respondent represents in the total Indian population, are applied throughout so that, for example, a total population of 958,927,836 individuals is estimated across the same 583 districts. Aggregated estimates were checked wherever possible against NSSO's own reported state-level and national-level estimates (NSSO, 2006). Rounded weights were used to obviate the absurdity of fractions of individuals. This created a rounding error that reduced the total estimated population by just 0.01%; or a maximum of 0.06% for any one state. The two data sources are assumed to be sufficiently commensurate: under-five and infant mortality rates are not expected to have changed rapidly between 2001 and 2004.

Dependent variables

Two dependent variables are used. Rajan et al.'s (2008) calculations using census data provide the district-wise number of deaths per 1000 live births for infants less than one year of age and for children less than five years of age. Unsurprisingly, these alternative measures are closely correlated ($r = 0.967$, see Appendix B). Under-five mortality rate is selected for presentation below it provides a smoother data series. (Given their close correlation, the two series yield very similar results – available on request – with coefficient estimates in the same directions and the same pattern of statistical significance.)

To test the importance of non-materialist pathways in multi-level logistic models, self-reporting of 'ailment' by individuals is selected as the binary dependent variable. 'Ailment' here covers all health complaints, including accidents, in the 15 days before being surveyed whether or not they are diagnosed and/or treated. Such measures have been widely used and, importantly, capture the *perception* of malady which, even if not real, is considered crucial in non-materialist theories. In a review of the literature on self-reported measures of subjective well-being, including health, Stiglitz, Sen, and Fitoussi commend them despite their need for further development (2008:150–51; see also Krueger & Schkade, 2008). We operationalize the measure in three ways: for all individuals, for men only, and for women only, since gender may be an important factor in self-reported health. One salient weakness of self-reported measures is their dependency on culture. We use state-level fixed effects to control for state-level variations in culture (see below).

Other variables

All income-variables are derived from NSSO data on monthly consumption expenditure per capita over the month before survey date (used interchangeably with 'income' henceforth). For each district, average income is the estimated mean of individual incomes. Poverty gap is the income-weighted proportion of the district population with incomes below a threshold of 60% of the estimated national mean, with the largest weights attaching to individuals with the greatest shortfall below this threshold. (For example, an individual with income Rs. 10 less than the 60% threshold is given a weight of 10, one with a shortfall of Rs. 20 a weight of 20, etc.) Poverty gap expresses the depth of material deprivation, reflecting the higher likelihood of ill health effects attaching to the lowest incomes in materialist theory. A 60% threshold is somewhat arbitrary but captures a reasonable portion of the estimated population (26.7%, compared with 5.9% with a 40% threshold, and 0.1% with a 20% threshold). Poverty gap has the added benefit of being much less strongly correlated with average income levels than headcount ratios and therefore obviates issues related to multicollinearity (Appendix B). Income inequality is the estimated Gini coefficient of all incomes in a district. (Across the 17 major states it ranged from 7.2 in Nainital district, Uttarakhand, to 46.7 in Sundargarh district, Odisha.) It is highly correlated with percentile ratios but has the advantage of capturing the entire (estimated) income spectrum in a district.

NSSO data also provide a variable for general education in eleven ascending categories ranging from illiteracy to graduate-level and above. District-wise literacy, the rate of individuals in category 2 (literate) and above, is introduced as a control to highlight the prevalence of under-five mortality among the illiterate as well as the poor. Models that substitute literacy with average education – the mean of individual education scores across a district – are also estimated. These models are then re-estimated using specifically female/male literacy and average education.

Other control variables, such as employment rates or public hygiene and sanitation, are eschewed for two reasons, following Pritchett and Summers (1996) and Biggs et al. (2010:268–269). First, since there are multiple mechanisms linking income-variables to health, we exclude other controls to capture the whole effect. Second, to obviate multicollinearity: variables such as average income and public health are likely to be correlated with several other societal variables.

Appendix C presents descriptive statistics for the main district-level variables used.

Data treatment

Rajan et al.'s (2008) district-wise under-five and infant mortality rates were used untreated and little cleaning of NSSO data was necessary. A small number of missing values and some outlying income outturns (0.47% of the surveyed sample of 383,346) were removed to reduce spurious variation. There were 180 households that reported zero consumption expenditure but given India's poverty these are likely to be genuine and were not removed. Since incomes were heavily skewed towards the lowest (skewness 13.8), outliers were removed only from the top of the range. High incomes were removed from districts whose ratio of standard deviation to mean was more than 2.0 (covering 97.7% of assumed normal distributions). Incomes higher than Rs. 80,000 (the 99.99th percentile) were also removed. These two criteria removed just 64 outliers. All cleaning reduced the total sample size by less than 0.49%, lowered the sample mean income by 0.45%, but reduced the standard deviation of incomes by 12.01%. Trial histograms showed all calculated district-level variables to be mildly skewed. Data were not transformed, however, because taking logs increased the skew of inequality, the variable of chief interest (although it reduces skews of other independent variables). (Log–log models were also estimated and produced similar results but are not presented – see note in Table 2.)

State-level fixed effects

State-level fixed effects are used in district- and individual-level models to control for substantial cultural, physical, and public policy variations across India's states (see Zimmerman, 2008, on 'unobserved confounders' – although these arguments are most germane to longitudinal analyses). India's states are organised mainly along linguistic-cultural lines. Diet and lifestyle vary widely (compare rice-based, low fat diets in Tamil Nadu with wheat-based, high-fat diets in Punjab; alcohol is prohibited in five states, including Gujarat), as do climate and geography (compare warm winters in Kerala with freezing ones in Uttar Pradesh; Odisha's forest cover with Rajasthan's desert). Also, the positive association between 'health-consciousness' at state-level and the perception, and therefore reporting, of ailment in India is well-established (NSSO, 2006:18–20). With high education levels and good healthcare infrastructure, Kerala, for example, stands out as highly health-conscious and reports markedly higher rates of ailment. State-level fixed effects, then, also control for differences in health consciousness, state-level provision of public goods, including access to and quality of healthcare, and state social spending.

As well as being theoretically sound, state-level fixed effects are pragmatic. A Hausman test of consistent and efficient estimators under fixed and random effects for Model 18 (Table 2) returns a large score of 165.00 ($p = 0.000$), reflecting the substantial differences in coefficient magnitudes under fixed and random effects. Using state-level fixed effects in a cross-sectional study of districts such as this is equivalent to estimating a multi-level model in which states are assigned dummy variables. The several statistically significant coefficients estimated for these state-dummies – only two were statistically insignificant ($p > 0.050$) – corroborate the Hausman test and underscore the importance of controlling for state-level effects. Random effects models, then, generate biased estimates since state-level variations powerfully influence the relationship under study. Note, however, that under random effects the direction of coefficients and their statistical significance at 95% confidence does not change. The difference in the size of coefficient estimates may be partly because fixed effects models block the (materialist) investment in infrastructure pathway at state-level. But since this is only one of several possible state-level mechanisms, and given the large difference in coefficients estimates (reflected in the large Hausman test score), we opt to use fixed effects models and thereby focus this analysis on district-level mechanisms.

Hypotheses and models

The central policy debate addressed by this paper is expressed in the following hypotheses:

H1. Controlling for average incomes, under-five mortality rates across Indian states/districts are positively associated with income inequality levels.

H2. Controlling for average incomes, under-five mortality rates across Indian states/districts are positively associated with poverty gaps.

H3. Controlling for average incomes, under-five mortality rates across Indian states/districts are negatively associated with literacy rates.

H1, H2 and H3 are tested with linear regression models first at state-level, then at district-level with state-level fixed effects. These models do not assume any specific causal mechanism. To study the importance of inequality on measures of well-being through specifically non-materialist pathways a multi-level hypothesis is generated:

H4. Controlling for district average income, individual income, and individual education, the higher the level of inequality in the district in which an individual lives, the more likely s/he is to report an ailment.

A multi-level logistic regression model is developed to test H4. State-level fixed effects again account for unspecified cross-state variances. There is no poverty term: personal protection of health depends on personal income and is theoretically independent of exposure to district-level poverty. District- rather than state-level income inequality is used since individuals can be expected to be more sensitive to inequality across their district than across their state (the mean population across the 583 districts in the cleaned NSSO sample is 1.6 million, compared with 27.3 million for states). But these are applied to the surveyed sample – not estimated population – of over 380,000 individuals across 583 districts.

Results and interpretation

Inequality and public health – state-level

Regressing state-level infant mortality rates on net state domestic product per capita across India's 35 states and Union Territories returns a negative coefficient (Model 1, Table 1). Inequality is neither significant by itself nor once income is controlled (Models 2, 5). Average income, poverty rate, and literacy by themselves are all statistically significant, and literacy has the largest effect (Models 1, 3, 4). Poverty, a positive associate, loses its significance once income is controlled (Model 6), and income loses its significance once literacy is controlled (Model 7). When all four variables are included only literacy remains statistically significant (Model 9 – estimating Model 9 with only the 17 major states reduces literacy's statistical significance, $b_1 = -1.016$, $p = 0.080$).

Inequality and public health – district-level

Regressing district-level under-five mortality rates on average income and income inequality produces results in line with standard materialist theory (Models 10, 11, 14, Table 2). Average income

Table 1
Coefficient estimates of state-level infant mortality rates linearly regressed on state-level net state domestic product per capita, poverty rate, income inequality, and literacy rate (with standard errors and p-scores); all states and Union Territories.[a,b]

	Single variables				Pairwise comparison with NSDP/cap			All income-variables/all	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
NSDP/cap	**−0.008**** **(0.002)**	–	–	–	**−0.009***** **(0.002)**	**−0.006*** **(0.002)**	−0.002 (0.003)	**−0.007*** **(0.003)**	−0.002 (0.003)
Inequality	–	0.584 (0.692)	–	–	1.085 (0.673)	–	–	0.814 (0.701)	0.944 (0.595)
Poverty	–	–	**0.835**** **(0.260)**	–	–	0.509 (0.303)	–	0.395 (0.317)	0.243 (0.272)
Literacy	–	–	–	**−1.197***** **(0.218)**	–	–	**−1.116**** **(0.321)**	–	**−1.079**** **(0.311)**
Adjusted R^2	0.259	0.000	0.215	0.462	0.296	0.301	0.459	0.309	0.478
N	32	35	35	35	32	32	32	32	32

[a] Standard errors in parentheses. ***p-score < 0.001, **p < 0.010, *p < 0.050. All results with p < 0.05 are considered statistically significant and are in bold.
[b] All linear terms, for regressand and regressors.

Table 2
Coefficient estimates of district-level under-five mortality rates linearly regressed on district-level average income, income inequality, poverty gap, and literacy rate (with standard errors and p-scores); state-level fixed effects.[a,b,c]

	Single variables				Pairwise comparison with average income			All income-variables/all	
	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Average income	**−0.028***** **(0.004)**	–	–	–	**−0.027***** **(0.004)**	**−0.026***** **(0.004)**	**−0.011**** **(0.004)**	**−0.022***** **(0.005)**	−0.005 (0.005)
Income inequality	–	**−0.366***** **(0.103)**	–	–	−0.062 (0.107)	–	–	−0.190 (0.120)	−0.145 (0.113)
Poverty gap	–	–	**0.368***** **(0.082)**	–	–	0.151^{+} (0.085)	–	**0.221*** **(0.096)**	**0.202*** **(0.090)**
Literacy rate	–	–	–	**−0.572***** **(0.052)**	–	–	**−0.480***** **(0.062)**	–	**−0.475***** **(0.062)**
Adjusted R^2	0.739	0.711	0.715	0.765	0.739	0.740	0.768	0.741	0.770
N	479	479	479	479	479	479	479	479	479

$^{+}$Coefficient estimate close to statistical significance: $p = 0.077$.
[a] Mortality rates calculated by Rajan et al. (2008) using 2001 census data; all other variables calculated by authors using survey data from NSSO 60th round in 2004.
[b] Standard errors in parentheses. $^{***}p$-score < 0.001, $^{**}p < 0.010$, $^{*}p < 0.050$. All results with $p < 0.05$ are considered statistically significant and are in bold.
[c] All linear terms, for regressand and regressors. Log–log models returned similar results, with statistically significant coefficient estimates in the same directions and slightly higher R^2 values of ~ 0.800. The splitting of the poverty term into a log-term and a dummy term (= 1 when poverty is zero, to deal with ln[0] in 42 districts) makes the coefficients less straightforward to interpret. (The dummy poverty term effectively becomes a coefficient of wealth.)

is negatively and significantly associated with under-five mortality. Income inequality's apparent negative association, however, is due to its correlation with average income ($r = 0.279$). Once average income is controlled for, the inequality coefficient becomes statistically insignificant ($p = 0.560$). H1 cannot be accepted: controlling for average income, income inequality is not a predictor of public health. Poverty gap is strongly and positively associated with under-five mortality (Model 12). (Note that poverty's larger coefficient estimate is mainly due to arbitrary differences in measurement units: using daily rather than monthly income would increase the average income coefficient roughly 30-fold.) Again, however, controlling for average income renders the poverty estimate statistically insignificant (Model 15), albeit at a strict 95% confidence level ($p = 0.077$) – H2 cannot be accepted. Controlling for both average income and inequality, however, a strong and significant coefficient is again estimated for poverty (Model 17).

Once literacy rate is controlled for in Model 16, the effect of average income, with which it is strongly correlated ($r = 0.654$), becomes much weaker – H3 is accepted. Moreover, literacy is a stronger predictor of under-five mortality than even poverty (both are measured as percentages). Including all variables, average income is rendered statistically insignificant and only poverty and literacy remain as strong predictors of under-five mortality (Model 18). Substituting literacy rate alternatively with female or male literacy rates ($r = 0.868$) does not substantially affect the non-income coefficient in Model 18 (female: $b_1 = -0.431$, $p = 0.000$; male: $b_1 = -0.406$, $p = 0.000$). Replacing literacy rate with average education, female average education, or male average education, however, produces much smaller non-income coefficients ($b_1 = -0.103$, $p = 0.000$; female: $b_1 = -0.093$, $p = 0.000$; male: $b_1 = -0.084$, $p = 0.000$; female/male average education are again highly correlated, $r = 0.892$).

Inequality and self-reported health – individual-level

Logistic regression of individual-level self-reported health on district-level inequality with state-level fixed effects returns large and statistically significant odds ratios greater than 1 (Model 19, Table 3). Larger odds ratios are returned for women than for men in gender-specific estimations. Introducing district average income, individual income, and individual education as controls substantially attenuates the odds ratios but they remain high and above 1 (Model 20) – H4 is accepted. Again, larger estimates are returned for women than for men.

Discussion

Pro-market liberalizers emphasise the need for further increases in Indian average incomes and can point to differences across states. Our state-level results support their position: inequality is not a significant predictor of public health at this level once average income is controlled. We do not replicate James and Syamala's (2010) finding, based on 1990s Indian state-level data, that controlling for per capita income, inequality becomes a positive predictor of child mortality. Controlling for literacy, however, we find the effect of average income becomes statistically insignificant. Nevertheless, the state is a highly aggregated analytical unit. India's largest state, Uttar Pradesh, had a population of over 166 million in 2001; its smallest 'major state', Chhattisgarh, had a population of almost 21 million. In addition, their number provides little statistical power. This study's findings at district-level may be more illuminating.

Model 17, using only income-variables, provides strong evidence for the materialist explanation of variances in public health across Indian districts. Average income and poverty – key materialist variables – have statistically significant effects on public

Table 3
Individual reports of ailment in 15 days before survey logistically regressed on district-level inequality: odds ratios (with standard errors and *p*-scores); state-level fixed effects.[a,b]

	Model 19			Model 20: Controlling for district average income, individual income and individual education		
	All	Men	Women	All	Men	Women
District inequality	**5.752***** **(0.563)**	**5.167***** **(0.704)**	**6.465***** **(0.908)**	**1.834***** **(0.201)**	**1.610**** **(0.247)**	**2.116***** **(0.334)**
N^c	381,475	194,755	186,720	381,114	194,565	186,579

[a] Standard errors in parentheses. ***p-score < 0.001, **$p < 0.010$, *$p < 0.050$. All results with $p < 0.05$ are considered statistically significant and are in bold.
[b] All linear terms, for regressand and regressors.
[c] Sample sizes are smaller in Model 20 due to missing education data.

health in the expected direction and income inequality does not. The model predicts that *ceteris paribus* it would take roughly Rs. 45 more per month in average consumption expenditure or a five percentage point narrowing of the poverty gap for one less under-five death per thousand live births. For a 'typical' district with average consumption expenditure of Rs. 557 per month and poverty gap of 18% (the respective averages across the 479 districts), this translates to an 8% rise in average incomes or a 25% reduction in poverty gap.

Even if Model 17 predicted perfectly (an adjusted R^2 value of 0.741 is high but far from perfect), reducing poverty by 25% may be as difficult as raising average incomes by 8% – which should policy focus on? Introducing another broad – and non-income – measure of development complicates the policy debate. Including literacy in Model 18 suggests the average income variable is capturing the effects of poverty and literacy. But whereas it would still take a five percentage point decrease in poverty to save one under-five per thousand, it would take only a two percentage point increase in literacy. For the typical district with a literacy rate of 55%, this translates to a 25% reduction in poverty gap or just a 4% increase in literacy.

Our district-level analysis highlights two caveats to the straightforward 'wealthier is healthier' policy prescription. First, public health is indeed undermined by material deprivation but literacy, another tractable (non-income) form of disadvantage plays an important role too. Although wealthier is healthier, wealth cannot be understood simply in terms of average income. Second, the effect of average income levels is indirect: higher average incomes may improve public health but only through reduced poverty and improved literacy. To this extent the distribution of income and other development goods does matter. Note also that although we find no statistically significant association between inequality and public health, inequality may affect public health by effectively sustaining poverty, not only through purely distributional effects but over time by reducing the growth elasticity of poverty – see Kapoor (2013) whose longitudinal study was at Indian state-, not district-level.

The small differences between female and male literacy variables' predictive powers suggest that in the early 2000s child mortality across these 479 districts was slightly more strongly associated with women's literacy and education than with men's. More germane to this study's central concern, however, is the much larger difference between literacy and average education variables, which underscores the efficacy of focussing on the most disadvantaged rather than on improving the average. Substituting literacy with average education calculated from NSSO data in Model 9 repeats the pattern at state-level: the non-income coefficient is attenuated ($b_1 = -0.246$, $p = 0.000$). Literacy may act as a floor, capturing the minimum skill – or 'functional health literacy' – required to understand medicine labelling, access healthcare, and engage with public health programmes (Nutbeam, 2000:263–265).

Although income inequality may not predict under-five or infant mortality, it may still affect social well-being via non-materialist pathways. Individual-level logistic models estimate exposure to district-level income inequality is associated with a much greater likelihood of an individual reporting an ailment in the 15 days before being surveyed. Controlling only for cross-state variations in unspecified variables, a unit-increase in district inequality – or a 4% increase in inequality for the 'typical district' with Gini coefficient 0.23 (the average across the 583 districts) – is associated with an odds ratio of 5.8 for an individual reporting ailment. With district average income and individual income controlled to capture the materialist pathways of level of district development (investment in infrastructure) and individual ability to protect health, and individual education controlled to capture individual health consciousness as well as the protective effects of education, these odds are substantially attenuated. But they remain high: the same 4% increase in inequality is still associated with an 83% increase in the odds of an individual reporting ailment. Since the model's controls include the chief variables of materialist theory, this is tentative evidence that increased inequality has a negative effect on individual well-being via non-materialist pathways. Re-estimating these models by gender returns higher odds ratios for women than for men. Women in high inequality districts are almost twice as likely as men to report an ailment. This corroborates similar findings elsewhere of poorer self-reported health among women (Case & Paxson, 2005).

Conclusions

Standard policy prescriptions for improving public health in less developed countries focus on raising average income levels since it is widely accepted that 'wealthier is healthier'. Only after the 'epidemiological transition' is inequality hypothesized to become a significant predictor of health. In the case of India in 2004 wealthier is indeed healthier. But our analysis suggests it is low poverty and high literacy rather than wealth *per se* that improves public health. Infant mortality rates are negatively associated with average income levels and positively associated with poverty at both state- and district-level. Inequality, however, is not associated with public health at state- or district-level, where linear regression models controlling for average income and variations in unspecified state-level variables show income inequality is not a statistically significant predictor of infant or under-five mortality rates. But controlling for poverty gap and literacy rate renders the average income coefficient statistically insignificant too. This implies that expanding economic output improves public health not by raising average income but by reducing poverty and increasing literacy – undermining the dominant pro-market liberalization position and supporting the pro-poor position. Moreover, of the two predictors, literacy has a markedly stronger effect than poverty. These models are not designed to isolate any particular causal mechanism but their estimates are in line with materialist theory, operating at both societal- and individual-level (investment in health infrastructure and personal protection of healthcare).

The analysis, however, also finds evidence for the negative affect of inequality operating through non-materialist pathways, even in this LDC before the 'epidemiological transition.' Multi-level logistic models that control for district average income and individual income, the chief materialist variables, and for individual education show both men and women are more likely to self-report an ailment if exposed to higher district-level inequality. This evidence is, however, only tentative: other pathways, such as elite capture of public health resources in high inequality districts, cannot be dismissed.

These findings have important policy implications. First, although wealthier is indeed healthier, policymakers should focus on alleviating poverty rather than simply raising average incomes to improve public health. Second, addressing other (non-income) development issues such as illiteracy may be more effective than raising incomes. Policy must also be more subtle. While inequality cannot predict infant or under-five mortality rates, it is strongly connected to self-reported health, even in a major LDC. Economic policies narrowly focused on growth, therefore, may be insufficient. They must be coupled with a broader understanding of societal well-being and the factors that promote it.

Limitations

This study complements existing work by focussing on a less developed country at district-level, and using a multi-level model, as recommended by Subramanian and Kawachi (2004). It is, however, clearly limited and much further work is needed. An obvious lacuna is an understanding of how the associations analysed here have changed over time, especially important in a fast-changing LDC like India. Time-series data could also reveal how long average income and poverty take to manifest in health outcomes ('incubation' periods may be longer via societal-level pathways than via individual-level pathways); and whether these effects are mediated by changes in, rather than levels of, inequality (as reported for Latin America by Biggs et al., 2010). Second, focussing on 17 major states neglects several interesting cases, including Delhi, the rich and unequal capital, and the sparsely populated and less developed districts of India's north east. Third, income-variables derived from consumption expenditure data are likely to underestimate the true extent of inequality (as well as average income and poverty). Fourth, the causal connections underlying these results must be crystallised by connecting inequality directly to the intermediary outcomes implicated by theory, for example, levels of investment in public healthcare for a materialist, societal-level theory or individuals' levels of stress-related hormones for a non-materialist, individual-level theory. Ethnographic studies, especially those built on social capital theory, may more fully address the changes in health-affecting and/or health-reporting behaviours that inequality brings about, how these changes vary across close-knit and loosely associated groups, how they vary across groups of different sizes (in 2001 the populations of districts in India's major states ranged from 21 thousand to 9.4 million), and what they are contingent on (including public health programmes). Such studies could in turn develop the underlying theory, locating points of interdependence between individual- and societal-level, and materialist and non-materialist mechanisms.

The expanding literature on the sociology of health, nonetheless, should help turn policymakers' attention away from simple metrics of success like GDP growth and towards a more qualified understanding of social priorities.

Acknowledgement

We are indebted to two anonymous reviewers for their thoughtful comments and suggestions.

Appendix A. Infant mortality rate, net state domestic product per capita, and poverty pate across Indian states and union territories

	State	Population[a]	% of India pop	IMR[b]	NSDP/capita[c]	Poverty rate[d]	Inequality[e]	Literacy rate[f]
	India	1,028,737	100	58	24,143	28	32.3	64.8
1	**Uttar Pradesh**	**166,198**	**16**	**72**	**12,840**	**33**	**28.1**	**56.3**
2	**Maharashtra**	**96,879**	**9**	**36**	**35,915**	**31**	**34.8**	**76.9**
3	**Bihar**	**82,999**	**8**	**61**	**7759**	**41**	**22.0**	**47.0**
4	**West Bengal**	**80,176**	**8**	**40**	**22,654**	**25**	**32.4**	**68.6**
5	**Andhra Pradesh**	**76,210**	**7**	**59**	**25,321**	**16**	**32.9**	**60.5**
6	**Tamil Nadu**	**62,406**	**6**	**41**	**30,105**	**23**	**33.1**	**73.5**
7	**Madhya Pradesh**	**60,348**	**6**	**79**	**15,442**	**38**	**27.4**	**63.7**
8	**Rajasthan**	**56,507**	**5**	**67**	**18,565**	**22**	**26.8**	**60.4**
9	**Karnataka**	**52,851**	**5**	**49**	**26,745**	**25**	**30.8**	**66.6**
10	**Gujarat**	**50,671**	**5**	**53**	**32,021**	**17**	**30.1**	**69.1**
11	**Odisha**	**36,805**	**4**	**77**	**17,380**	**46**	**30.7**	**63.1**
12	**Kerala**	**31,841**	**3**	**12**	**31,871**	**15**	**30.1**	**90.9**
13	**Jharkhand**	**26,946**	**3**	**49**	**18,512**	**40**	**27.4**	**53.6**
14	**Assam**	**26,656**	**3**	**66**	**16,782**	**20**	**23.8**	**63.3**
15	**Punjab**	**24,359**	**2**	**45**	**32,948**	**8**	**27.2**	**69.7**
16	**Haryana**	**21,145**	**2**	**61**	**37,842**	**14**	**25.3**	**67.9**
17	**Chhattisgarh**	**20,834**	**2**	**60**	**18,559**	**41**	**27.5**	**64.7**
18	Delhi	13,851	1	32	61,560	15	28.8	81.7
19	Jammu & Kashmir	10,144	1	49	21,314	5	23.9	55.5
20	Uttarakhand	8489	1	42	24,740	40	29.8	71.6
21	Himachal Pradesh	6078	1	51	32,564	10	27.4	76.5
22	Tripura	3199	0	32	24,394	19	32.6	73.2
23	Meghalaya	2319	0	54	23,793	19	21.6	62.6
24	Manipur	2294	0	14	18,527	17	16.0	70.5
25	Nagaland	1990	0	17	20,234	19	19.1	66.6
26	Goa	1348	0	17	76,426	14	27.6	82.0
27	Arunachal Pradesh	1098	0	38	27,271	18	32.0	54.3

(continued on next page)

(*continued*)

	State	Population[a]	% of India pop	IMR[b]	NSDP/capita[c]	Poverty rate[d]	Inequality[e]	Literacy rate[f]
28	Pondicherry	974	0	24	48,573	22	34.7	81.2
29	Chandigarh	901	0	21	74,442	7	28.3	81.9
30	Mizoram	889	0	19	24,662	13	23.0	88.8
31	Sikkim	541	0	32	26,693	20	24.8	68.8
32	Andaman & Nicobar Islands	356	0	19	40,921	23	24.2	81.3
33	Dadra & Nagar Haveli	220	0	48		33	27.4	57.6
34	Daman & Diu	158	0	37		11	19.2	78.2
35	Lakshadweep	61	0	30		16	20.5	86.7
ALL STATES – Correlation with IMR[g]					**−0.532****	**0.488****	0.145	**−0.692*****
N					**32**	**35**	35	35
17 MAJOR STATES – Correlation with IMR[g]					**−0.611****	0.442	−0.435	**−0.727*****
N					**17**	**17**	**17**	17

Major states are in bold.
[a] Population figures from 2001 census.
[b] Infant mortality rates from Sample Registration System, Registrar General (India). 2004 data.
[c] Net state domestic product per capita from Central Statistical Organisation (India). As at 2004, current prices.
[d] Poverty rate from Databook For Deputy Chairman, Planning Commission of India. 2004 data.
[e] Income inequality calculated by authors as Gini co-efficient of monthly consumption expenditure per capita data from 60th round of National Sample Survey Office survey. 2004 data.
[f] Literacy rate from Office of the Registrar General. 2001 data.
[g] $^{***}p$-score < 0.001, $^{**}p < 0.010$, $^{*}p < 0.050$.

Appendix B. Correlation matrix of district-level variables (based on cleaned data)[a]

		Income inequality			Poverty at 60% of national mean[c]			Mortality rates	
$N = 583$[b]	Average income	Gini	90/10 ratio	80/20 ratio	Poverty rate	Poverty gap	Literacy	MR < 1 yr	MR < 5 yr
Average income	**1.000**								
Gini	**0.279**	**1.000**							
90/10 ratio	**0.275**	**0.763**	**1.000**						
80/20 ratio	**0.333**	**0.764**	**0.783**	**1.000**					
Poverty rate	**−0.718**	0.035	0.013	−0.013	**1.000**				
Poverty gap	**−0.277**	**0.211**	**0.204**	**0.181**	**0.413**	**1.000**			
Literacy	**0.654**	**0.168**	**0.155**	**0.155**	**−0.596**	**−0.177**	**1.000**		
MR < 1 yr	**−0.496**	**−0.189**	**−0.120**	**−0.098**	**0.500**	**0.333**	**−0.519**	**1.000**	
MR < 5 yrs	**−0.488**	**−0.180**	**−0.113**	**−0.104**	**0.467**	**0.320**	**−0.507**	**0.967**	**1.000**

[a] Statistically significant results ($p < 0.05$) are in bold.
[b] For all correlations with mortality rates $N = 479$, covering the 17 major states (95% of India's total population).
[c] National mean is the (unweighted) mean of monthly consumption expenditure per capita across the estimated population of India.

Appendix C. Descriptive statistics of main district-level variables used

	Under-five mortality rate (per 1000 live births)	Average income (Rs per month)	Income inequality (Gini)	Poverty gap (%)	Literacy (%)
17 major states (*N* = 479)[a]					
Mean	70.67	557.33	23.72	18.26	55.33
Median	67.00	519.30	23.31	18.45	55.63
Standard deviation	24.67	205.69	6.43	8.41	14.42
Maximum	136.00	2201.60	46.75	45.59	99.15
Minimum	14.00	209.42	7.24	0.00	10.19
All states and Union Territories (*N* = 583)[a]					
Mean	–	584.99	23.25	18.16	58.21
Median	–	538.42	22.82	17.40	58.39
Standard deviation	–	219.88	6.76	12.20	15.25
Maximum	–	2201.60	52.57	100.00	99.15
Minimum	–	209.42	5.85	0.00	10.19

[a] 'Major states' includes the 479 districts in the 17 largest states by population, together accounting for 95% of the population and none of which individually account for less than 1%. 'All states and Union Territories' includes all 583 districts across all 35 states and Union Territories surveyed by NSSO.

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