Education and household inequality change

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Education and household inequality change: a decomposition analysis for India

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RESEARCH MEMORANDUM

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Abstract

Previous studies show that rising returns to education have lead to higher wage inequality in developing countries. However, given the importance of non-wage employment and indirect effects of education through labour supply and fertility choices, a similar relationship does not necessarily hold for inequality between households. Based on a decomposition analysis for India, we find counteracting impacts of education on household expenditure inequality. Declining returns to education of household heads reduced inequality, driven by the self-employed. In contrast, rising returns to spouses' education increased inequality in urban areas. We also find that changes in education levels increased rural and urban inequality, due to persistently high illiteracy. Finally, the indirect effect on fertility had a small equalizing impact in urban areas, but slightly increased inequality in rural areas.

Key words: Education, inequality, regression-based decomposition, India

***JEL* codes:** O15, D63

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1. Introduction

Inequality is rising in many developing countries, but the determinants of changes in inequality are not well understood. Recent research, both theoretical and empirical, has focused on the individual earnings distribution (for example, Feenstra and Hanson, 1997; Zhu and Trefler, 2005; Goldberg and Pavcnik, 2007). Due to skill-biased technical change and international trade demand for high-skilled labour is growing faster than supply, raising the returns to education. This appears to be the major cause of rising earnings inequality in developed and developing countries.

But does a similar relationship also hold for household inequality? Household welfare is more relevant from a welfare perspective than individual income: resources are, at least to some extent, shared among household members. As such, household inequality measures are more representative of a country's inequality situation and an important characteristic of the development process.[2] Household inequality, defined as inequality of household income or consumption expenditure, differs from individual earnings inequality in level as well as changes. For industrialised countries differences have been ascribed to, for example, increased working hours of married women and changes in government benefits (see Gottschalk and Smeeding, 1997; Gottschalk and Danziger, 2005). The relative importance of these and other factors will be country-specific, but for developing countries in general there are two main reasons why education is related differently to household inequality than to earnings inequality.

First and foremost, besides earnings from formal employment, households have income from other sources. This is especially important in developing countries where a large part of workers is self-employed in the informal sector. The self-employed are often excluded in studies of the individual earnings distribution, but their returns to education are likely to be lower than for employees. Moreover, the education level of self-employed is lower, on average, than of formal sector employees (Van der Sluis *et al.*, 2005). Rising wage-returns to education may tell us little about household inequality if a large part of household income is earned outside wage employment.

[2] For a discussion, see Atkinson and Bourguignon (2000: 34).

Second, education has indirect effects on income, for example through labour supply, occupational choices, and fertility decisions (Ram, 1989). These factors could leave the individual earnings distribution unaffected, but they do matter for household inequality. For example, if higher education increases labour force participation of women, this will increase income of households with highly educated women. If these are relatively affluent households, household inequality will rise even if the earnings distribution is unchanged. A positive effect of education on an individual's earnings is thus only part of the total returns to education.

Compared to the many detailed studies on earnings, much less attention has been paid to changes in household inequality. Existing cross-country empirical evidence shows a weak relationship between education and household inequality (Ram, 1989; De Gregorio and Lee, 2002), which is not surprising given the multitude of factors that play a role. In this paper we focus on the increase in household expenditure inequality in India between 1993-1994 and 2004-2005. India has experienced rapid growth since the economic reforms of the early 1990s and several studies of the earnings distribution show that rising returns to education are the main cause for increased earnings inequality (for example, Kijima, 2006). India is an important case to study inequality beyond the distribution of earnings, since a large share of workers is self-employed.[3] Moreover, India has one of the most unequal education distributions in the world. Given the widespread attention to inequality of earnings due to education so far, it is highly relevant to ask how much and how education has actually contributed to the increase in household inequality.

The increase in household inequality in India is decomposed using household survey data and a regression-based method developed by Bourguignon *et al.* (2008). With this method it is possible to distinguish different channels through which education and other household or individual characteristics are related to household inequality. Like the standard Oaxaca-Blinder decomposition, it separates the distributional effect of changes in characteristics themselves versus changes in the returns to these characteristics. Rather than explaining differences in means between two distributions,

[3] Dasgupta (2003) shows there is no relationship between earnings and education among street vendors in Delhi, based on data collected in 1995. However, nationally representative data on self-employment earnings are not structurally collected in India.

however, the Bourguignon-method decomposed changes in the entire distribution. In contrast to other methods that compare full distributions (Juhn *et al.,* 1993; DiNardo *et al.*, 1996; Machado and Mata, 2005), this method focuses explicitly on the household income distribution, incorporating changes in individuals' occupational choice and earnings, and in household composition. As such, direct and indirect effects of education can be measured.

The Bourguignon-method has been applied to a number of East Asian and Latin American countries in Bourguignon *et al.* (2005) and Ferreira and Leite (2004). These in-depth country studies show that the indirect effects of education can matter for household inequality. The present study focuses specifically on the role of education, rather than asking more generally which factors explain observed changes in inequality. In the analysis we distinguish the returns to education, direct and indirect effects of educational attainment, and the role of different household members.

Our results show that declining returns to education of household heads had an equalizing effect in both rural and urban India. In urban India this is driven by the household heads that are self-employed, which stresses the importance of taking into account non-wage income in inequality analyses. As opposed to household heads, returns to education of spouses increased urban inequality. This finding suggests that female earnings and labour force participation are important for inequality dynamics, but more research on the relationship between women's education and labour supply is needed. Further, we find that changes in educational attainment had a strong adverse direct effect on inequality, due to the persistently high prevalence of illiteracy. This underlines the importance of expanding schooling for the poorest households in India. In addition, the indirect effect of education through fertility changes increased rural inequality, because the number of children declined less in poorer households. In urban India the indirect effect was opposite: inequality decreased somewhat because poorer households had, on average, a greater decline in the number of children. An improvement in the distribution of education could stimulate a more equalizing effect of fertility changes as well.

After describing inequality and other key characteristics of India in section 2, the Bourguignon-method is discussed in section 3. Section 4 summarises estimation results that are part of the decomposition analysis, and in section 5 the final decomposition results are discussed. Finally, section 6 concludes.

2. Inequality in India

To measure household inequality, one can use either income or expenditure data. For India, only household expenditure is available, as recorded in the National Sample Survey Organization (NSSO) Consumer Expenditure survey. Inequality in consumption expenditure can be viewed as more permanent inequality than income inequality, as consumption expenditure is affected by households' ability to use savings, borrowing, or insurance arrangements to buffer shocks in income. Since survey data always refer to a limited time period, consumption expenditure reflects living standards more accurately than income (see Deaton and Zaidi, 2002).

In a recent paper, Datt and Ravallion (2009, Table 2) show that consumption inequality in India increased significantly after 1991, when major reforms took place: the trend changed from negative to positive in rural India and from zero to positive in urban India. Table 1 shows the Gini coefficient and Theil index for inequality in monthly per capita expenditure[4] (household consumption expenditure divided by household size, henceforth *MPCE*) in 1993-94 and 2004,-05[5] which both increased in rural and urban India. Although growth in income levels reduced poverty in the 1980s and especially after the reforms in the 1990s, the increase in inequality in the post-reform period adversely affected the poor (Dhongde, 2007).

Table 1: Inequality of Monthly per Capita Expenditure

	Rural		Urban	
Year	Gini	Theil	Gini	Theil
1993	29.4	18.0	35.4	24.8
2004	30.7	20.8	37.4	28.1

Note: Figures based on 17 major states plus urban Delhi.
Source: NSSO Consumer Expenditure survey

[4] In constant prices and spatially deflated, based on the price indexes by Deaton (2003) for 1987-1999 and the official Consumer Price Index for Agricultural Labour and Consumer Price Index for Industrial Workers for 1999-2004. Deaton's indexes are more carefully calculated than the official national price indexes, but are only available at the state level until 1999.

[5] Henceforth 1993 and 2004. These 'thick' survey rounds use the same reference period, whereas the survey in 1999-2000 used mixed reference periods. It is by now well-established that this affected measures of poverty and inequality, so the 1999-2000 measures are not comparable (see Deaton and Drèze, 2002).

The distribution of earnings in India has been studied in detail. Chamarbagwala (2006) finds that in the period 1983-1999, relative demand shifted to more high-skilled workers especially in the service sector, causing a considerable increase in the wage gap between high- and low-educated workers. Dutta (2006) also finds evidence for a widening wage gap between graduate and primary education (for regular salaried employees), contributing to the rise in wage inequality in the 1990s. Kijima (2006) considers changes in both the returns to education and in educational attainment of male urban fulltime workers. She finds that between 1983 and 1993 the latter accounted most for increased earnings inequality. Between 1993 and 1999, on the other hand, earnings inequality increased mostly due to rising returns to higher education caused by within-industry demand shifts. There seems to be no doubt the wage gap between low- and high- skilled workers in India has grown, in line with the experience of many other countries. Due to data limitations, however, analyses of the earnings distribution include only wage workers or even a subsample of them, while about 40 per cent of the urban labour force and 55 per cent of the rural labour force is self-employed. Female workers are also excluded from most studies, though female labour supply is an important issue in India's development. According to Chamarbagwala (2006: 2003), especially highly educated women entered the labour force during the 1980s and 1990s, though other studies stress more poverty-induced female participation (for example Raikhy and Mehra, 2003). All in all, women's earnings matter for household income and inequality, but little is known about their distribution and the role of education.

Apart from Kijima (2006), not much attention is paid to the distributive effect of changing educational endowments in India. With over 30 per cent of the adult population illiterate, India has a very unequal distribution of education, and much scope for improvement. According to Kochhar et al. (2006) and Mazumdar and Sarkar (2008) government policies have been biased towards higher education, devoting insufficient resources to improving and expanding lower education. The government of India realises that investment in higher education is necessary to enable further growth, but expanding basic education is necessary to reduce inequality (Government of India, 2008). From a policy perspective, therefore, it is also important to know to what extent educational endowment changes affect household inequality.

The distribution of educational attainment in 1993 and 2004 is summarised in table 2. Educational attainment is substantially higher in urban than in rural India and higher for males than for females. During this period schooling levels have increased, but the share of illiterate adults remains high.

Table 2: Educational attainment in India, percentage distribution

	Rural				Urban			
Education level completed	Male		Female		Male		Female	
	1993	2004	1993	2004	1993	2004	1993	2004
Illiterate	45.85	35.03	75.54	63.82	17.91	13.25	40.10	31.03
Below primary	14.68	9.62	7.91	6.53	10.86	6.22	9.93	6.69
Primary	12.46	15.27	7.16	10.85	12.49	12.54	11.85	11.87
Middle	12.32	18.62	5.23	10.08	15.91	19.45	12.23	15.91
Secondary	11.66	16.11	3.55	7.05	26.73	27.03	16.60	20.55
Graduate or above	3.04	5.34	0.61	1.68	16.10	21.51	9.28	13.96
Total	100	100	100	100	100	100	100	100

Note: Figures are based on all individuals of age 20 and higher.
Source: NSSO Consumer Expenditure survey

As suggested by Ram (1989), the increased schooling of women may lead to a reduction in fertility. Education of women is generally negatively related to fertility, because desired family size declines and the ability to achieve the planned number of children improves with education. Between 1981 and 1991, women's education and child mortality were the most important factors explaining fertility differences across Indian states and over time (Drèze and Murthi, 2001). Since household expenditure is measured on a per capita basis and children typically do not generate much income for the household, fewer children are associated with higher per capita expenditure. Changes in the average level and distribution of education among women could therefore affect household inequality through changes in fertility. The NSSO data show that during 1993-2004 there was a decline in the average number of children per household (table 3). In both years, beyond the level 'Below primary', higher educational attainment is associated with a lower number of children. Over time, the average number of children declined at all educational levels. Average household size (not shown) did not decline during this period, due a small increase in the number of males and females older than 20.

Table 3: Average number of children per household, by female education level

Average education level females	Rural		Urban	
	1993	2004	1993	2004
Illiterate	2.04	2.03	2.06	1.88
Below primary	2.17	2.02	1.92	1.91
Primary	1.99	1.80	1.81	1.62
Middle	1.79	1.64	1.66	1.45
Secondary	1.60	1.46	1.42	1.29
Graduate and above	1.23	1.09	1.17	0.95
Total	1.96	1.88	1.62	1.43

Note: Children are household members of age 15 or younger. Educational level is the average of all adult females in the household. The total average includes households with no adult females. *Source*: NSSO Consumer Expenditure survey.

3. Method and Application

After discussing the decomposition framework and some India-specific considerations in section 3.1, the empirical strategy is explained in more detail in section 3.2

3.1 Decomposing changes in household inequality

Bourguignon et al. (2005) and Bourguignon et al. (2008) develop a microeconometric decomposition of changes in the household income distribution that is designed to analyze household income inequality. The method is a generalization of the decomposition developed by Oaxaca (1973) and Blinder (1973), who separate inequality of mean income between groups into differences in characteristics, differences in returns to characteristics, and differences in the residual or unobserved factors. Using micro-economic data, the decomposition can be applied to the entire distribution of income, rather than their means. The difference with DiNardo *et al.* (1996) and Juhn *et al.* (1993) is that the level of analysis is the household rather than the individual, while is does account for individuals' characteristics. Education, labour force participation and earnings are modeled at the individual level and household income is the sum of its members' earnings, plus non-earnings income.

To decompose changes in inequality into endowment effects (the effect of changes in the distribution of household characteristics) and price effects (the effect of changes in the returns to these characteristics), distributional counterfactuals are constructed. Let $f^t(y)$ be the distribution of *MPCE* in year *t*. *X* is a vector of household characteristics, and $\chi^t(X)$ is the joint distribution of all elements of *X* in year *t*. Denoting $g^t(y|X)$, the distribution of income conditional on *X*, the marginal distribution of *MPCE* in year *t* can be expressed as:

$$f^t(y) = \int g^t(y|X)\chi^t(X)dX \ . \tag{1}$$

The change in the distribution of *MPCE* between two years is thus a function of the change in $g(y|X)$ (the price effect) and the change in $\chi(X)$ (the endowment effect).

The empirical equations are explained below, but for now note that expenditure of household *h* in year *t*, y_{ht}, is a function of the vector X_{ht} of household characteristics. Further, y_{ht} depends on the vector β_t of parameters reflecting the returns to those characteristics, on the vector ε_{ht} of unobservable characteristics, the vector γ_t of parameters reflecting educational attainment, and vector θ_t of parameters reflecting fertility choices.

$$y_{ht} = F(X_{ht}, \beta_t, \varepsilon_{ht}, \gamma_t, \theta_t) \ . \tag{2}$$

A change in household income, due to a change in one or some of the components of Eqn. 2, leads to a change in the distribution of income $f^t(y)$. The impact of each component can be simulated by replacing it by its counterpart of another year, say from year *t*=0 to *t*=1. For example, the vector β_0 is replaced by β_1 while keeping everything else constant. This gives:

$$y_{h0}(\beta_1) = F(X_{h0}, \beta_1, \varepsilon_{h0}, \gamma_0, \theta_0) \ . \tag{3}$$

The contribution of the change in β to the total change in the income distribution (the so-called price effect) is then simply

$$f_\beta^{\,0\to 1}(y) - f^0(y) \ . \tag{4}$$

The same analogy applies to the other components of Eqn. 2. Since the entire distribution is simulated, the difference can be evaluated based on any measure of inequality.

Although the decomposition compares separate cross-sections, rather than following households within a panel dataset, the data requirements for this method are high. Ideally, one has individual earnings data and characteristics such as age and education, as well as household level non-earnings income and characteristics such as household size and composition. For India, there is no dataset that combines individual level earnings and employment details with household level income. The National Sample Survey on employment and unemployment (the usual source of earnings data for India) does not record earnings for self-employed workers or total household income. Since a large part of workers is self-employed, total recorded household earnings are not even representative for actual household income from labour. Due to these data restrictions, household inequality analysis is based on the consumer expenditure survey. This survey offers a reliable measure of welfare (*MPCE*), but no individual employment and earnings details. Fortunately, the consumer expenditure survey does report individuals' level of educational attainment, age, and gender, and principal employment status, industry, and occupation of the household head. These characteristics are used in the analysis, as explained below.

Using these expenditure data means individual earnings and labour supply decisions cannot be estimated. The household-returns to education therefore include wage-returns and the effect of education on hours worked and industry or sector of employment. In other words, the estimated household-returns to education include direct and indirect effects, except for those controlled for (number of children and the household heads' employment status, industry, and occupation).

3.2 Empirical Strategy

All data are obtained from the NSSO Consumer Expenditure surveys of 1993-94 and 2004-05, and are in 1993-94 constant prices and spatially deflated. To measure the price and endowment effects on the distribution of *MPCE*, parameters β, γ, and θ, and the residuals ε need to be estimated. This section gives the three empirical equations and describes in more detail how the price and endowment effects of education are obtained.

First of all, *MPCE* is regressed on household characteristics, separately for rural and urban households:

$$\ln(MPCE_{ht}) = X_{ht}\beta_t + \varepsilon_{ht}\,, \tag{5}$$

where the vector X_{ht} is specified in Appendix table A.1. Table A.2 shows the OLS estimation results.

Second, the educational attainment level is estimated by an ordered probit model, with six different levels of education: (1) Illiterate; (2) Literate below primary school; (3) Primary school complete; (4) Middle school complete; (5) Secondary or higher secondary school complete; and (6) Graduate and above. Educational attainment X^E is estimated separately for the head, the spouse, and other members, and separately for rural and urban areas:

$$\Pr\left[X_{it}^{E} = k\right] = F\left(\alpha_{k,t} - X_{it}^{-EF}\gamma_t\right) - F\left(\alpha_{k-1,t} - X_{it}^{-EF}\gamma_t\right), \tag{6}$$

where i is the individual, $k(=1,\ldots,6)$ is the highest education level completed, and F is the standard normal cumulative distribution function. The cut-off values α_{kt} are estimated along with the regression parameters γ_t. The vector X_{it}^{-EF} includes gender, age (in linear splines), social group, religion, and state. The number of children is not included in this vector because education is itself an explanatory variable in the model for number of children.

For the number of children, X^F, an ordered probit model is estimated at the household level, separately for rural and urban areas:

$$\Pr\left[X_{ht}^{F} = m\right] = F\left(\alpha_{m,t} - X_{ht}^{-F}\theta_t\right) - F\left(\alpha_{m-1,t} - X_{ht}^{-F}\theta_t\right), \tag{7}$$

Where the number of children $m=1,\ldots,12$ and F is again the standard normal cumulative distribution function. The vector X_{ht}^{-F} includes gender and age of the head, number of adult females, average age of adult females in linear splines, average education of adult females, social group, religion, and state. Since the data do not allow us to identify which children belong to which mother, age and education are averaged over all adult females (20 years or older) in the household.

Now, to obtain the price effect of education, a counterfactual distribution is constructed using 1993-94 as the base year. This is year t=0, while 2004-05 is year t=1. For each year, the vector of coefficients $\hat{\beta}$ in Eqn. 5 is estimated, and residuals are stored in $\hat{\varepsilon}$. Next, in the base-year vector $\hat{\beta}_0$, the coefficients for all education dummies are replaced by their counterparts from the end-year vector $\hat{\beta}_1$. The resulting vector is $\hat{\beta}_{sim}$. Finally, the value of $MPCE$ is simulated for each household using base-year characteristics and unobservables: $\ln(MPCE_{h,sim}) = X_{h0}\hat{\beta}_{sim} + \hat{\varepsilon}_{h0}$. The distribution of simulated *MPCE* is the so-called counterfactual distribution. The difference between inequality in the 1993-94 distribution and inequality in the counterfactual distribution is the contribution of the price effect of education to inequality. The price effects of other variables are calculated in a similar way in order to assess the relative importance of education.

To find the endowment effect of education on the distribution of *MPCE*, a counterfactual distribution is obtained by changing educational attainment in X_{ht} in Eqn. 5. The educational attainment of individuals in the base-year sample is 'updated' by simulation, based on the conditional distribution of education on individual characteristics. First, using Eqn. 6, the base-year vector of characteristics X_{i0}^{-EF} is multiplied by the end-year coefficient vector $\hat{\gamma}_1$. Combined with the end-year cut-off values $\hat{\alpha}_{k,1}$, a simulated level of education is obtained for each individual. The simulated level of educational attainment replaces the original value in the base- year vector of characteristics X_{h0}, which gives $X_{h,sim}$. A simulated value of *MPCE* for each household is obtained using base-year returns to characteristics and unobservables: $\ln(MPCE_{h,sim}) = X_{h.sim}\hat{\beta}_0 + \hat{\varepsilon}_{h0}$.

Finally, to include the indirect effect of education through fertility changes, the number of children is also updated for each household, using Eqn. 7 in the following way. First, the simulated level of educational attainment is used to replace the original values in X_{h0}^{-F}. The simulation vector of characteristics $X_{h,sim}^{-F}$ is used to obtain a simulated number of children, with the base-year coefficients $\hat{\theta}_0$ and cut-off values $\hat{\alpha}_{m,0}$. Then, both simulated education and simulated number of children replace their original values in the base-year vector of characteristics X_{h0} in Eqn. 5, and again a simulated value of *MPCE* is found for each household, using $\ln(MPCE_{h,sim}) = X_{h.sim}\hat{\beta}_0 + \hat{\varepsilon}_{h0}$.

4. Estimation Results

Before turning to the decomposition results in section 5, the estimation results of the three empirical equations are presented. For the consumption equation, the discussion is focused on the returns to education, in section 4.1. Then the education and fertility estimations results are briefly described in section 4.2.

4.1 Returns to Education

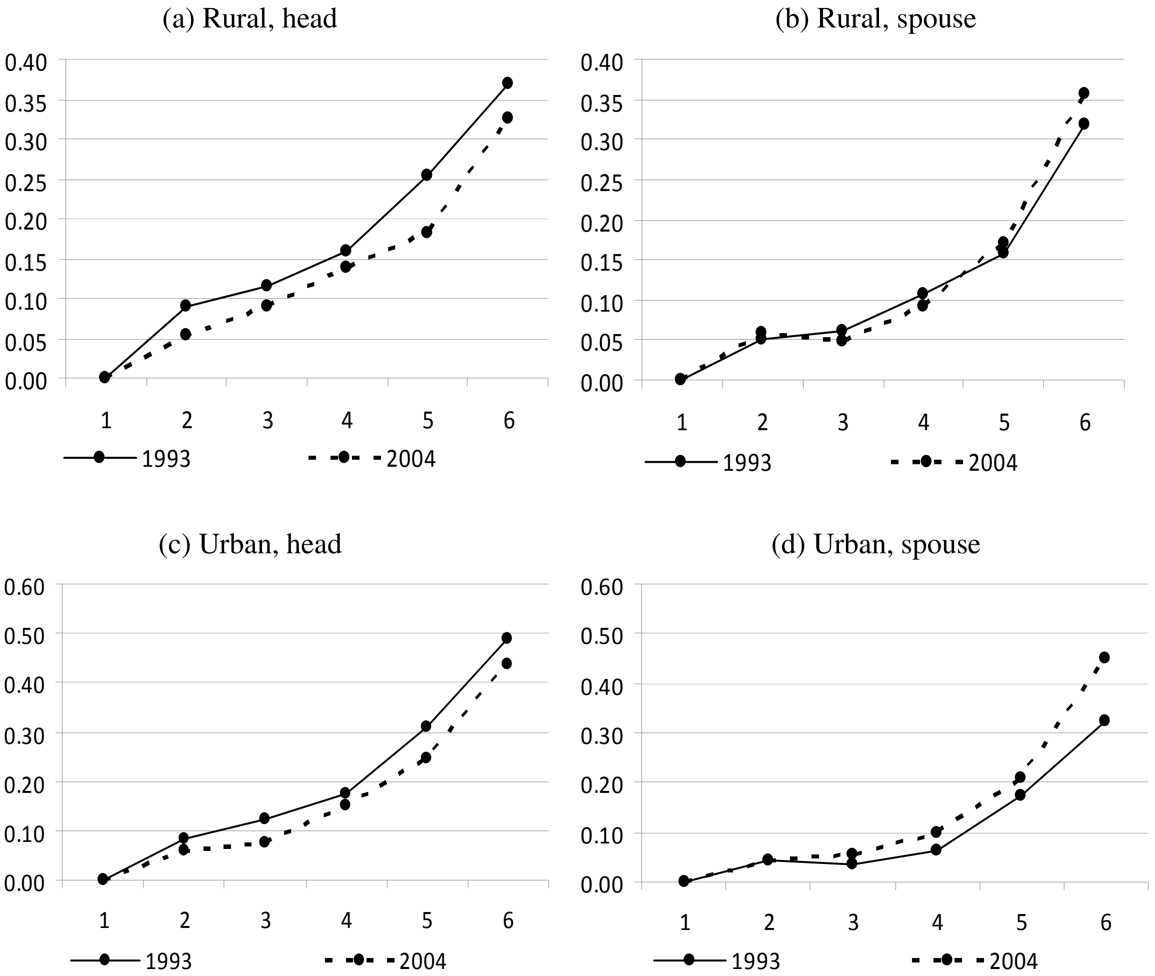
The household-returns to education are estimated in the consumption expenditure regression. When estimating household per capita expenditure, education level dummies are included separately for the household head, spouse, and (the average of) other members, with illiterate as reference category. The estimated coefficients for these variables indicate the household-returns to education, which are different from the returns to education estimated in a standard wage equation (wage-returns to education). In the present analysis, the household-returns to education include multiple possible ways in which education is associated with household expenditure, of which earnings is only one part. Other effects may run through labour participation and hours of work, which are not controlled for separately, or efficiency in production in the family business.

Figures 1 shows the coefficient estimates for education of the household head and spouse in rural and urban India, respectively. For the household head, both rural and urban household-returns to education declined at all levels (compared to zero returns for the illiterate). This means that differences in expenditure between households with high- and low-educated heads became smaller during 1993-2004. Although between some adjacent education levels the difference in returns increased (for example between secondary and graduate education in rural India), overall the returns became less dispersed.

The picture is quite different for the spouses' household-returns to education. During 1993-2004 the structure of returns clearly became more convex, especially in urban India. The difference in expenditure level between households with low- and high-educated spouses thus increased over the period.

The returns to education of other members (not shown) were only about half those for the head and spouse, and turn out to have negligible impact on household inequality. For inequality, the education coefficient estimates suggest that the price effect of education will differ between the head and spouse of the household: especially in urban India, where they have changed in opposite directions. This is a first indication that rising earnings inequality may explain little of the increase in household expenditure inequality. Whereas the wage-returns to education increased for males and females in rural and urban India, the household-returns are different.

Figure 1: Estimated returns to education, household head and spouse



Source: NSSO Consumer Expenditure survey and author's calculations.

4.2 Education and fertility

In principle, the models for education and fertility in this analysis are used to obtain information on their conditional distributions, to be able to simulate endowment changes. Because education and number of children are explanatory variables in the *MPCE* equation, consumption expenditure itself is not included as explanatory variable in either the education or the fertility model. For this reason, these models cannot be regarded as proper economic models (see Bourguignon *et al.* (2005) for more discussion). Nevertheless a short discussion of the estimation results seems appropriate.

In total, 12 ordered probit models of educational attainment were estimated: one for each year for rural and urban India, and for the head, spouse, and other household members separately. The results for household head and spouse are summarised in appendix tables A.3 and A.4. All results show that females have lower education than males, as do individuals belonging to a backward social group (scheduled caste or tribe), though the disadvantage of scheduled caste members declined between 1993 and 2004. Also, Muslims have on average lower education than Hindus, while Christians and other non-Hindus have significantly higher education levels.

The results for number of children are summarised in appendix table A.5. These indicate that a higher average education level of adult females is associated with a lower number of children in the household. At higher levels of education the negative effect becomes larger, so the negative relationship is stronger. This could indicate that as female education levels rise, average fertility rates will fall more at higher levels of education, which could increase inequality.

We now turn to the results of the decomposition analysis, comparing actual and counterfactual distribution to measure the various distributive effects of education.

5. Decomposition Results

In the decomposition analysis the price effects of all characteristics and the endowment effect of education (with and without the indirect effect through changes in the number of children) are simulated. An important note here is that the total change in the distribution cannot be decomposed additively into the changes of the components in Eqn. 2. Still, the size and direction of the price and endowment effects can be compared to each other and to the total change in inequality, in order to determine the relative importance of each. Another issue is that the results depend on which year is chosen as base-year. The choice of base-year determines, for example, at which distribution of characteristics (X_h) the price effect (the change in β) is evaluated. For the price effect,

$$f_\beta^{\,0\to1}(y) - f^{\,0}(y) \neq f^{\,1}(y) - f_\beta^{\,1\to0}(y), \quad (8)$$

and this applies to all components. In other words, the contribution to inequality made by one specific component is sensitive to the order in which the components are analyzed, which is a problem of path dependency. Devicienti (2009) shows that each component's Shapley-value can be calculated as the average of its contribution to inequality across all possible decomposition paths. However, since we look at educational attainment of the household head, spouse, and other members separately, as well as the indirect fertility effect, the number of different possible decomposition paths is large, and calculating the Shapley-value is quite cumbersome. Instead, we focus on two decomposition paths. The first path uses 1993 as base-year, measuring the contribution of each component when it is first in the decomposition path. The second path uses 2004 as base-year, measuring the contribution of each component when it is last in the decomposition path. The average of both paths is reported as well. The distributions are summarised using the Gini coefficients, but other measures, including the log deviation and the Theil index, give similar results.

Table 4: Decomposition inequality change 1993-2004

	Rural			Urban		
	Path 1	Path 2	Average	Path 1	Path 2	Average
Gini 1993	29.4	29.4	29.4	35.4	35.4	35.4
Gini 2004	30.7	30.7	30.7	37.4	37.4	37.4
Total change	1.3	1.3	1.3	2.0	2.0	2.0
Price effects						
Total	0.3	0.3	0.3	0.6	1.2	0.9
Age	0.1	0.1	0.1	-0.1	0.1	0.0
Education all	-0.4	-0.4	-0.4	0.2	0.6	0.4
__head	-0.3	-0.4	-0.4	-0.5	-0.5	-0.5
__spouse	0.0	0.0	0.0	0.7	0.9	0.8
__others	0.0	0.0	0.0	0.0	0.1	0.1
Children	0.0	0.0	0.0	-0.1	-0.1	-0.1
Household size	0.0	0.0	0.0	-0.1	-0.1	-0.1
Social group	0.1	0.1	0.1	0.1	0.1	0.1
Religion	0.0	0.1	0.1	0.0	0.0	0.0
Status	0.2	0.1	0.2	0.1	0.2	0.1
Occupation	0.2	0.2	0.2	0.0	0.0	0.0
Industry	-0.2	-0.3	-0.2	0.2	0.2	0.2
State	0.3	0.4	0.4	-0.3	-0.1	-0.2
Endowment effects						
Education all	0.3	0.5	0.4	-0.1	0.7	0.3
__ head	0.1	0.2	0.2	-0.2	0.3	0.0
__ spouse	0.2	0.2	0.2	0.1	0.5	0.3
__ others	0.1	0.0	0.1	0.0	0.0	0.0
Educ. all + children	0.6	0.5	0.5	-0.2	0.5	0.2

Note: 1993 is base-year in Path 1, 2004 is base-year in Path2. *Source*: Author's calculations based on NSSO Consumer Expenditure survey

The first two rows in table 4 show inequality observed in 1993 and 2004, while the other rows show the difference in Gini coefficient between the counterfactual distribution and the base-year distribution. Both rural and urban inequality increased in this period, and all price effects combined ("Total") increased inequality by about one third of the total increase. Compared to other household characteristics (except for State in rural India[6]) changing household-returns to education had the largest impact on household inequality.[7]

In rural India, changes in the returns to education reduced inequality even though observed inequality increased. It is entirely driven by the returns to education of the household head, while the price effect of spouses' and others' education is zero. This is in line with the changes in coefficients shown in figure 1(a) and 1(b). In urban India the price effect of household head's education is equalizing as well. However, this is more than offset by the price effect of spouses' education (see figure 1(c) and 1(d)). The total price effect of education is therefore positive in urban India.

The negative price effect of education of the head is surprising. In the earnings literature, increased inequality among workers has been ascribed to rising returns to education, especially at higher educational levels. The household analysis suggests that in household consumption expenditure, differences associated with education of the household head have actually become smaller. It is the spouse's education that has become more important for household consumption, increasing urban inequality. This issue will be discussed further at the end of this section.

The endowment effect of education is positive in both rural and urban India, which means changes in education attainment levels contributed to higher inequality. The urban endowment effect is driven mainly by the spouses, though the two decomposition paths give quite different results.[8] For both periods, a mobility matrix can be made comparing base-year and simulated education levels. The simulation shows what education level a person from the 1993-sample would have if he or she was in the 2004-sample (or the other way around, depending on the choice of bas-year), *given* his or her age,

[6] The positive price effect of state indicates between-state divergence of rural households' expenditure, after controlling for the other household characteristics. This could reflect, for example, differences in state-level welfare policies or in agricultural productivity.
[7] The price effects of education are robust to the specification of the MPCE equation: the results are similar when only age, education, household size, state and survey subround are included as regressors.
[8] This is due to several factors: differences in the simulation of education itself, differences in prices at which these endowment changes are evaluated, and differences in the distribution of other household characteristics.

gender, social group, religion, and state. An example is given below in table 5 for the education of spouses in rural India, according to path 1. As this matrix shows, most progress in terms of educational attainment is made by individuals who are literate and completed up to middle school (levels 2, 3, and 4). This pattern appears in all simulations; for rural and urban, for heads, spouses, and other members. On average, relatively little progress is made by the group of illiterates, which explains why the direct endowment effect of education was to increase inequality. It implies there is scope for improvement in the distribution of education and household expenditure, by focusing more on expanding schooling for the lowest class.

Table 5: Simulated education mobility matrix, spouses in rural India

Simulated level 2004 Education 1993	1	2	3	4	5	6	Total
1 – Illiterate	86.7	8.6	4.8	0	0	0	100
2 – Below primary	0.1	6.0	80.4	13.4	0	0	100
3 – Primary	0	0	15.3	80.8	3.9	0	100
4 – Middle	0	0	0	29.8	70.1	0.1	100
5 – Secondary	0	0	0	0	68.8	31.3	100
6 – Graduate and higher	0	0	0	0	0	100	100

Source: NSSO Consumer Expenditure survey and author's calculations.

Finally, the effect of changes in the number of children is added to the direct endowment effect of education, which is shown in the bottom row of table 4 ("Educ. all + children"). The indirect effect increases rural inequality further, but is equalizing in urban India as the combined direct and indirect endowment effect is smaller than the direct endowment effect. Among rural households, those with higher initial expenditure level have a higher increase in the average female education level in path1 (in path 2 there is no clear association). Consequently, there also appears a slightly negative relationship between initial expenditure and change in the number of children (the decline is larger for richer households), which is why inequality rises. In urban India, average female education increases most in the bottom half of the initial expenditure distribution, in both paths. Among urban households, therefore, the number of children declines more in households with lower initial expenditure, reducing inequality.

5.2 Total returns versus earnings-returns to education

Our results indicate that during 1993-2004 the change in returns to education increased urban inequality. This is in line with many previous studies that found that rising wage-returns to education caused higher wage inequality. However, the effect on household expenditure inequality was caused entirely by higher and more convex returns to education of the spouse. Returns to education of the head actually declined and became more equal. In rural India, as well, returns to education of the household head declined and contributed to a reduction in inequality. Although several studies have shown that earnings inequality increased in the 1990s due to rising wage-returns to education, for household heads the opposite is found at the household level.

A possible explanation is that the returns to education outside wage-employment declined (that is, in self-employment). Earnings inequality research for India and many other countries is based on wage-employees only, since often no earnings data are available for the self-employed. Since about a third of the urban and half of the rural household heads are self-employed, changes in self-employed earnings are likely to substantially influence the results. To test this, the decomposition analysis was done again separately for "employee" and "non-employee" households. For urban employee households (head is a regular or casual worker) the price effect of the head's education is indeed positive, though small, in line with earnings studies. In contrast, the effect is strongly negative for the non-employee households (head is self-employed or other), driving the results for urban India as a whole. This indicates that among urban households headed by a wage-employee, inequality associated with the head's education indeed increased. However, among urban households headed by a self-employed worker, inequality associated with the head's education level declined. Since this decline was relatively large, the overall price effect of the head's education was negative.

In rural India the price effect is negative for both employee and non-employee households. Regarding previous earnings studies, Kijima (2006) analyses only male urban fulltime workers, and studies that include both rural and urban workers do not estimate the returns to education for each group separately (Chamarbagwala, 2006; Dutta, 2006). Since their samples are dominated by male urban workers, these are likely to drive the results, and it is unclear how wage-returns to education changed among rural workers. All in all, the rising wage-returns to education appear to increase household inequality only among urban households headed by a wage-employee. For total urban and rural household inequality, changes in the returns to education of household heads were equalizing.

As opposed to urban household heads, returns to education of spouses increased urban inequality and dominate the total price effect of education. This could reflect increased female labour force participation, as the returns to education in any kind of employment are higher than in domestic work or unemployment. Also, more educated spouses may be more likely to enter the labour force. To shed light on this, table 6 shows principal activity status for urban spouses in 1993 and 2004.[9]

Table 6: Distribution of spouses according to principal activity status, urban India

				Change 1993-2004 by education level					
Principal status	1993	2004	Change	1	2	3	4	5	6
Self-employed	6.7	8.1	1.4	2.2	1.4	2.4	2.7	1.4	1.3
Regular employee	5.6	6.5	1.0	2.2	2.2	1.6	0.0	-5.6	-8.1
Casual worker	4.8	3.5	-1.2	-1.7	0.2	0.6	0.1	0.0	0.0
Unemployed	0.5	0.7	0.3	0.1	0.5	0.1	0.1	-0.3	-0.1
Other	82.5	81.1	-1.4	-2.8	-4.3	-4.8	-2.8	4.6	6.9
Total	100.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: Eduction level 1=illiterate, 2=below primary, 3=primary, 4=middle school, 5=secondary, 6=graduate and higher. *Source:* NSSO Employment and Unemployment survey, round 50 and 61.

The declining share of 'other', in column 3, indicates that relatively more spouses were in the labour force in 2004. It is likely that the shift into self-employment and regular employment increased the returns to spouses' education. However, the shift was actually opposite for spouses with secondary or higher education: the last two columns show that a highly educated spouse was less likely to be in the labour force in 2004 than in 1993. As noted in section 2, it is unclear how education and female labour force participation are related in India. As far as the NSSO survey data show, higher education is not associated with increased female labour force participation. Therefore, the increasing returns to

[9] Activity status of household members other than the head is not reported in the Consumer Expenditure survey, so cannot be accounted for in the decomposition analysis. Table 6 is based on the Employment and Unemployment survey to complement the decomposition results: it is based on a different sample, but both samples are nationally representative and cover the same time period.

education of spouses most likely reflect rising returns to education within activities, but more research is necessary to confirm this.

6. Concluding remarks

From the large body of research on earnings inequality we know that rising returns to education have led to higher earnings inequality in many countries, including developing countries. For household inequality, however, the role of education is less clear. In this paper we examine the relationship between education and household inequality dynamics in India over the period 1993-2004. A microeconometric decomposition of inequality changes shows the distributive effects of changes in returns to education, changes in educational attainment, and the indirect effect of the latter through fertility. The decomposition results indicate that changes in the returns to education reduced rural inequality and increased urban inequality, and their effect was large compared to other household characteristics associated with expenditure. The urban effect was driven by increasing returns to education of the spouse: both in rural and urban India the returns to education of the head declined and reduced inequality.

This is a surprising finding given that previous research on the earnings distribution in urban India has shown that the wage-returns to education increased after 1993, causing higher earnings inequality (Chamarbagwala, 2006; Dutta, 2006; Kijima, 2006). A possible explanation for this difference is that the returns to education in self-employment are lower than in wage-employment. This is confirmed when the decomposition is done separately for employee- and non-employee-households: the returns to education of the head only increase for urban employee-households, while they decline for non-employee households. Taking into account non-employees thus appears to be crucial when studying the evolution of household inequality.

Contrary to the household head, the returns to spouse's education increased urban inequality. This may be due to the fact that the share of spouses active in the labour market increased. However, labour force participation actually declined among the highest educated spouses, so the rising returns to education most likely reflect increasing returns to education within activities. Clearly, the role of education in women's labour force participation and earnings should be further studied in future research.

Changes in educational attainment increased both rural and urban inequality. Other studies have found that a distribution-neutral increase in average educational attainment can increase inequality (see Bourguignon *et al.,* 2005) due to the convex relationship between education and earnings. The present study of India shows a more alarming picture, namely, that rising educational attainment increased household inequality because the inequality of education itself increased. The simulation results indicate that educational attainment is only slowly improving for the large group of illiterate adults, and much faster for literates with some education. To reduce household consumption inequality, and inequality of education itself, stimulating literacy appears to be essential. This may also lead to a more equalizing indirect effect of education through fertility, which was small but inequality-increasing in rural India.

In general, our study shows that household-level analysis provides new insights in addition to the abundant existing results from the earnings literature. It sheds more light on the relationship between education and household inequality, shows important differences between household members, and highlights the importance of labour market developments. We conclude, therefore, that research on individual earnings inequality needs to be complemented by further analysis at the household level to gain deeper insight into the dynamics of education and inequality. Especially the returns to education outside wage-employment and the role of education in female labour supply and earnings are important factors associated with household inequality.

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Appendix

Table A.1: List of explanatory variables in *MPCE* regression equation

Variable	Description
Age_head	Age of household head
Age_head_sq	Squared age of household head
Age_other	Average age other members
Age_other_sq	Squared average age other members
Female_head	Indicator variable for female head of household
Educh	Indicator variables for education level of household head
Educs	Indicator variables for education level of spouse
Educo	Indicator variables for average education level other members
Nchild	Number of children (age 0-15)
N16_19	Number of teenagers (age 16-19)
Nmale20_65	Number of male adults
Nfem20_65	Number of female adults
N65	Number of elderly
Social group	Indicator variables for scheduled caste, scheduled tribe, or other*
Religion	Indicator variables for Hindu*, Muslim, Christian, or other religion
Status	Indicator variable for principal employment status: self-employed*, casual labour, salaried labour, or other.
Occupation	Indicator variable for principal occupation : professional, administrative, or other*
Industry	Indicator variable for principal industry: ten industries
State	Indicator variable for State
Subround	Indicator variable for survey subround

Note: * indicates reference category in *MPCE* regression equation. For education the reference category is illiterate. For industry the reference category is agriculture. Casual and salaried labour is one category in the rural sample.

Table A.2: Household *MPCE* estimation results

Dependent variable is *ln(MPCE)*	Rural		Urban	
Variable	1993	2004	1993	2004
Age_head	0.006***	0.005***	0.007***	0.008***
	(0.001)	(0.001)	(0.002)	(0.002)
Age_head_sq	-0.000***	-0.000***	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Age_other	0.004***	0.004***	-0.005***	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
Age_other_sq	-0.000***	-0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female_head	-0.082***	-0.076***	-0.144***	-0.157***
	(0.012)	(0.014)	(0.016)	(0.022)
Educh_2	0.091***	0.054***	0.085***	0.061***
	(0.006)	(0.008)	(0.010)	(0.017)
Educh_3	0.116***	0.091***	0.125***	0.076***
	(0.007)	(0.007)	(0.011)	(0.013)
Educh_4	0.160***	0.139***	0.173***	0.151***
	(0.008)	(0.007)	(0.011)	(0.013)
Educh_5	0.254***	0.181***	0.311***	0.247***
	(0.010)	(0.009)	(0.012)	(0.015)
Educh_6	0.369***	0.326***	0.490***	0.439***
	(0.019)	(0.018)	(0.016)	(0.020)
Educs_0	0.165***	0.165***	0.240***	0.304***
	(0.009)	(0.012)	(0.014)	(0.019)
Educs_2	0.051***	0.059***	0.045***	0.045***
	(0.008)	(0.009)	(0.012)	(0.017)
Educs_3	0.060***	0.049***	0.035***	0.057***
	(0.009)	(0.009)	(0.011)	(0.013)
Educs_4	0.106***	0.091***	0.063***	0.098***
	(0.012)	(0.009)	(0.011)	(0.015)
Educs_5	0.157***	0.171***	0.172***	0.209***
	(0.022)	(0.015)	(0.013)	(0.016)
Educs_6	0.319***	0.357***	0.325***	0.449***
	(0.049)	(0.034)	(0.018)	(0.022)
Educo_0	0.139***	0.158***	0.145***	0.213***
	(0.007)	(0.008)	(0.013)	(0.018)
Educo_2	0.051***	0.033***	0.017	0.077***
	(0.008)	(0.011)	(0.016)	(0.024)
Educo_3	0.084***	0.057***	0.044***	0.055***
	(0.009)	(0.010)	(0.016)	(0.020)
Educo_4	0.139***	0.091***	0.077***	0.082***
	(0.011)	(0.010)	(0.015)	(0.020)
Educo_5	0.171***	0.157***	0.121***	0.144***
	(0.011)	(0.011)	(0.015)	(0.019)
Educo_6	0.245***	0.255***	0.187***	0.238***
	(0.036)	(0.020)	(0.018)	(0.022)
NChild	-0.086***	-0.085***	-0.112***	-0.108***
	(0.002)	(0.002)	(0.003)	(0.004)
N16_19	-0.016***	-0.022***	-0.057***	-0.060***
	(0.003)	(0.004)	(0.005)	(0.006)

Table A.2 continued

Nmale20_65	0.014***	0.008**	-0.007	-0.008
	(0.004)	(0.004)	(0.005)	(0.007)
Nfemale20_65	-0.006	-0.004	-0.034***	-0.030***
	(0.004)	(0.005)	(0.006)	(0.008)
N65	0.006	0.022***	-0.023**	-0.029**
	(0.007)	(0.008)	(0.011)	(0.013)
SC	-0.100***	-0.102***	-0.094***	-0.112***
	(0.005)	(0.006)	(0.010)	(0.011)
ST (ref=other social group)	-0.139***	-0.165***	-0.090***	-0.094***
	(0.008)	(0.008)	(0.017)	(0.022)
Islam	-0.008	-0.008	-0.029***	-0.008
	(0.007)	(0.008)	(0.009)	(0.012)
Christian	-0.049***	0.059***	0.064***	0.034
	(0.015)	(0.018)	(0.018)	(0.022)
Other religion (ref=Hindu)	0.050***	0.061***	0.035**	0.149***
	(0.015)	(0.018)	(0.016)	(0.024)
Labour (rural)	-0.187***	-0.167***		
	(0.005)	(0.005)		
Salaried labour (urban)			0.022***	0.059***
			(0.008)	(0.010)
Casual labour (urban)			-0.202***	-0.188***
			(0.010)	(0.013)
Other status (ref=self-employed)	-0.013	0.069***	0.015	-0.036
	(0.011)	(0.015)	(0.019)	(0.034)
Professional	-0.044***	0.020	0.073***	0.075***
	(0.013)	(0.021)	(0.012)	(0.019)
Administrative (ref=other)	0.084***	0.147***	0.217***	0.220***
	(0.023)	(0.024)	(0.014)	(0.016)
Constant	5.854***	5.960***	5.747***	5.690***
	(0.031)	(0.037)	(0.046)	(0.061)
Observations	58787	59162	37293	33279
R-squared	0.331	0.391	0.489	0.518

Note: Dependent variable is the log of household real monthly per capita expenditure. Estimation by OLS, standard errors in parentheses. Sig *** p<0.01, ** p<0.05, * p<0.1. All estimations include dummies for industry, state, and survey subround. *Source*: NSSO Consumer Expenditure survey.

Table A.3: Results ordered probit estimation for education, household head

	Rural, head		Urban, head	
Variable	1993	2004	1993	2004
Female	-0.881***	-0.913***	-0.737***	-0.902***
	(0.022)	(0.025)	(0.029)	(0.040)
Age1	-0.014***	0.006	-0.011*	0.043***
	(0.004)	(0.005)	(0.006)	(0.007)
Age2	0.014***	-0.025***	0.023***	-0.050***
	(0.006)	(0.007)	(0.008)	(0.010)
Age3	-0.031***	0.008*	-0.034***	0.014**
	(0.004)	(0.004	(0.005)	(0.007)
Age4	0.014***	-0.012***	0.008**	-0.029***
	(0.003)	(0.003)	(0.007)	(0.005)
SC	-0.614***	-0.515***	-0.868***	-0.693***
	(0.015)	(0.016)	(0.025)	(0.027)
ST	-0.705***	-0.747***	-0.589***	-0.623***
	(0.020)	(0.024)	(0.049)	(0.056)
Islam	-0.500***	-0.449***	-0.709***	-0.730***
	(0.020)	(0.021)	(0.023)	(0.029)
Christian	0.246***	0.159***	0.352***	0.266***
	(0.037)	(0.040)	(0.042)	(0.054)
Other non-Hindu	0.102**	0.155***	0.233***	0.302***
	(0.044)	(0.047)	(0.041)	(0.051)
Cut-off values				
1	-0.583***	-0.860***	-1.186***	-0.883***
	(0.051)	(0.066)	(0.069)	(0.074)
2	-0.127**	-0.551***	-0.777***	-0.594***
	(0.051)	(0.066)	(0.069)	(0.075)
3	0.293***	-0.105	-0.408***	-0.165**
	(0.051)	(0.066)	(0.069)	(0.075)
4	0.774***	0.453***	-0.003	0.340***
	(0.051)	(0.066)	(0.069)	(0.074)
5	1.563***	1.238***	0.786***	1.068***
	(0.052)	(0.068)	(0.069)	(0.075)
Observations	58787	59162	37293	33279
Pseudo R2	0.06	0.05	0.05	0.05

Note: All estimations include state dummies. Standard errors are in parentheses. Sig *** p<0.01, ** p<0.05, * p<0.1.Age is measured in linear splines (marginal) 20-30, 30-40, and 40-50, 50+.
Source: NSSO Consumer Expenditure survey.

Table A.4: Results ordered probit estimation for education, spouse

	Rural		Urban	
Variable	1993	2004	1993	2004
Female	-0.441***	-0.564***	-0.489***	-0.356*
	(0.142)	(0.147)	(0.175)	(0.184)
Age1	-0.009**	-0.028***	0.019***	0.016**
	(0.003)	(0.004)	(0.004)	(0.007)
Age2	-0.012**	-0.002	-0.032***	-0.032***
	(0.005)	(0.006)	(0.007)	(0.010)
Age3	-0.014***	0.002	-0.014**	0.004
	(0.005)	(0.005)	(0.006)	(0.008)
Age4	0.019***	0.007	0.011**	-0.018**
	(0.005)	(0.005)	(0.006)	(0.008)
SC	-0.675***	-0.617***	-1.042***	-0.855***
	(0.021)	(0.020)	(0.030)	(0.033)
ST	-0.748***	-0.886***	-0.742***	-0.765***
	(0.031)	(0.030)	(0.066)	(0.072)
Islam	-0.437***	-0.502***	-0.769***	-0.697***
	(0.028)	(0.025)	(0.026)	(0.031)
Christian	0.392***	0.284***	0.447***	0.400***
	(0.045)	(0.045)	(0.047)	(0.056)
Other non-Hindu	0.191***	0.404***	0.340***	0.499***
	(0.057)	(0.059)	(0.044)	(0.053)
Cut-off values				
1	0.155	-0.889***	-0.881***	-1.054***
	(0.156)	(0.172)	(0.188)	(0.200)
2	0.525***	-0.640***	-0.588***	-0.835***
	(0.156)	(0.172)	(0.188)	(0.200)
3	1.003***	-0.147	-0.208	-0.464**
	(0.156)	(0.173)	(0.188)	(0.200)
4	1.541***	0.442**	0.216	0.022
	(0.156)	(0.174)	(0.188)	(0.200)
5	2.417***	1.321***	0.976***	0.801***
	(0.159)	(0.179)	(0.188)	(0.200)
Observations	48516	50565	28652	26769
Pseudo R2	0.11	0.10	0.06	0.05

Note: All estimations include state dummies. Standard errors are in parentheses. Sig *** p<0.01, ** p<0.05, * p<0.1. Age is measured in marginal linear splines 20-30, 30-40, and 40-50, 50+.
Source: NSSO Consumer Expenditure survey.

Table A.5: Results ordered probit estimation for household average number of children

	1993, rural			2004, rural			1993, urban			2004, urban		
Variable	Coef.	Std.		Coef.	Std.		Coef.	Std.		Coef.	Std.	
Female head	-0.378	0.018	***	-0.247	0.023	***	-0.367	0.028	***	-0.232	0.038	***
Age head	-0.002	0.000	***	-0.001	0.001	**	-0.003	0.001	***	-0.005	0.001	***
N females	1.010	0.030	***	1.251	0.040	***	0.985	0.052	***	1.070	0.070	***
Age1	0.237	0.004	***	0.274	0.005	***	0.279	0.007	***	0.270	0.010	***
Age2	-0.315	0.008	***	-0.389	0.010	***	-0.381	0.013	***	-0.401	0.016	***
Age3	-0.113	0.014	***	-0.101	0.017	***	-0.107	0.023	***	-0.070	0.024	***
females*age1	-0.108	0.004	***	-0.141	0.005	***	-0.137	0.007	***	-0.137	0.008	***
females*age2	0.130	0.007	***	0.184	0.008	***	0.175	0.010	***	0.188	0.013	***
females*age3	0.071	0.013	***	0.061	0.015	***	0.057	0.021	***	0.032	0.020	
Educf_0	0.238	0.041	***	0.468	0.062	***	-0.605	0.065	***	-0.660	0.129	***
Educf_2	-0.042	0.016	***	-0.120	0.019	***	-0.093	0.027	***	-0.044	0.040	
Educf_3	-0.146	0.019	***	-0.241	0.017	***	-0.194	0.024	***	-0.239	0.033	***
Educf_4	-0.254	0.026	***	-0.325	0.020	***	-0.334	0.025	***	-0.376	0.032	***
Educf_5	-0.362	0.032	***	-0.462	0.026	***	-0.509	0.024	***	-0.501	0.034	***
Educf_6	-0.653	0.084	***	-0.684	0.066	***	-0.800	0.031	***	-0.819	0.038	***
SC	-0.010	0.013		0.071	0.015	***	0.133	0.024	***	0.119	0.029	***
ST	-0.056	0.017	***	0.086	0.022	***	0.024	0.042		0.055	0.052	
Muslim	0.336	0.019	***	0.385	0.022	***	0.409	0.025	***	0.433	0.032	***
Christian	0.028	0.038		0.118	0.042	***	0.109	0.040	***	0.091	0.060	
Other	-0.015	0.036		0.011	0.045		0.001	0.042		-0.019	0.053	
Cut-off values												
1	0.242	0.049		0.819	0.061		0.398	0.082		0.337	0.096	
2	0.929	0.049		1.512	0.061		1.117	0.083		1.097	0.096	
3	1.628	0.050		2.296	0.062		1.885	0.083		1.982	0.096	
4	2.295	0.050		2.948	0.062		2.611	0.084		2.674	0.097	
5	2.890	0.051		3.505	0.063		3.197	0.084		3.183	0.099	
6	3.395	0.051		3.986	0.064		3.681	0.086		3.594	0.101	
7	3.828	0.053		4.430	0.066		4.114	0.089		3.949	0.106	
8	4.152	0.055		4.783	0.069		4.474	0.095		4.339	0.111	
9	4.441	0.058		5.067	0.073		4.709	0.104		4.663	0.119	
10	4.679	0.063		5.279	0.080		4.799	0.110		4.851	0.126	
11	4.879	0.069		5.489	0.091		4.980	0.129		5.029	0.140	
12	5.137	0.080		5.818	0.088		5.136	0.149		5.167	0.159	
N	58787			59162			37293			33279		
pseudo R2	0.10			0.12			0.15			0.15		

Note: All estimations include state dummies. Sig ***p<0.01, ** p<0.05. Age is measured in linear splines (marginal) 20-30, 30-40, and 40+. *Source*: NSSO Consumer Expenditure survey.