Schooling and household welfare: The case of Sri Lanka from 1990 to 2006

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Abstract

This paper looks at the effect schooling has had on household welfare in Sri Lanka during the 1990-2006 period, on average and across the welfare distribution. We account for the endogeneity of schooling using quantile instrumental variable estimation as developed in Chernozhukov at. al. (2015). We use pooled data from 4 cross section Household Income Expenditure Surveys. The results show that an extra year of schooling on the part of the most educated adult member in the household can increase welfare (proxied by real per capita consumption expenditure) by 3.8 per cent on average. However, the effect varies considerably across the welfare distribution: At the lower end, around the 20th and 25th quantiles, an extra year of education increases welfare by 6 and 5 per cent, respectively, while at the median it is around 3.5 per cent. At the higher, 90th quantile it is much less, at 1 per cent. Thus the marginal effect of schooling on welfare is significant and positive at all levels of the welfare distribution, but highest on the lower and middle quartiles. This result is different to findings in the literature that tend to show larger effects at higher quantiles, when endogeneity is uncorrected.

Keywords

Sri Lanka, Education, Welfare, Quantile Regression, Endogeneity

JEL Classification codes

I00 I20 I21 053.

1. Introduction

Sri Lanka is a developing country with deep and widespread schooling that has been well recognised in the literature. In the 1980s, for instance, it was recognised as being an 'outlier' amongst developing countries with levels of literacy that were much higher than can be expected at the given low income levels and high gender parity in education access and attainment (Isenman (1980), Sen (1981), Osmani 1994). More than thirty years (and a three-decade long civil war) later, in the 2000s, Sri Lanka still boasts of adult literacy levels even higher than before as stocks of those who completed secondary education has doubled and women surpass men in terms of education attainment (World Bank 2005).

Although many studies have looked at private returns to education at the *individual* level in Sri Lanka (Aturupane 1993; Gunawardane et. al. 2008; De Silva 2009; Himaz 2010, Himaz and Aturupane 2015), few studies look at how much an additional year of schooling contributes towards *household* economic welfare levels, proxied by consumption. This is an important aspect to look at because even though an extra year of education may lead to higher incremental returns at the individual level (on average around 5 per cent according to Himaz and Aturupane (2015)) this does not mean that incremental household welfare with respect to an extra year of education on the part of the most educated adult in the household (or some other proxy for the level of household education) is 5 per cent. This is because of a key problem that arises due to the accuracy of individual wage or earnings based estimations of returns to education in developing countries: In Sri Lanka, as in many developing countries, non-wage earners are a considerable share of the labour force, engaged in self employment activities or working for a family farm or venture earning an income for the household rather than the individual[1]. Since it is difficult to map an individual's

[1] In 1995/6, for example, only 56% of employed males and 54% of employed females were wage earners while 4% of males 16% of females were classified as unpaid family workers. In 2000/01 around 60% males and 49% of females were classified as wage earners while the rest classified as being in non-wage employment without

education attainment to their contribution to household income, surveys often assign household earnings as those attributable to the household head. Thus even if earnings are used instead of wages, the estimation of individual returns to education becomes problematic. In any case, individual returns estimation says little about household welfare and education or the effect education may have on welfare in rich versus poor households.

Several papers in the relevant literature such as Glewwe (1991) and Teal (2004) look directly at the impact of education on household welfare given prior asset accumulation and household characteristics, enabling an interpretation that suggests not simply a correlation but causality. Glewwe finds, for instance, that education has a positive effect on welfare for those employed in the public sector in Côte d'Ivoire. Teal finds that an extra year of education increased household welfare between 1.9 to 2.9 per cent in Ghana in the 1990s. Following an approach similar to Glewwe (1991) and Teal (2004), Rolleston (2011) finds not only that schooling plays an important role in household welfare in Ghana for the 1991-2006 period but that higher levels of schooling have larger and increasing benefits compared to lower levels of schooling. This type of result - that education significantly impacts household welfare (measured using real per capita consumption or income) - is evident in several other more recent studies as well such as Haddad and Maluccio (2003), Bellemare (2012), Alem and Söderbom(2012) and Aroura et. al (2015). A few papers also look at the impact of education on household consumption between poorer and richer households. For example, Nguyen et. al.(2007:477) uses Quantile Regression (QR) techniques to find, inter alia, that upper quantiles see larger increases in the marginal impact of education on household welfare in the South of Vietnam although comparable patterns are not evident in the North. In the North the impact is stable across the quantiles, apart from the very top. In a similar study for 12 Arab countries, Hassine (2015) finds that the marginal effect of education on household spending is generally larger at higher

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further classification in the Household Income and Expenditure Survey, a key data source collected by the country's Department of Census and Statistics.

quantiles. Himaz and Aturupane (2011) in a previous version of the current paper, used QR techniques for data from Sri Lanka to find that higher quantiles systematically enjoy greater incremental welfare to education levels between 9 to 13 years of schooling. A key drawback in the empirical specifications of these papers is that they do not account for endogeneity of education arising out of reverse causality (i.e., household welfare having a strong impact on education levels as shown in Dreze and Kingdon (2001) or Filmer and Pritchett (1999)) or the fact that there may be unobservable factors such as ability, motivation and attitudes correlated with both education levels and the error term, that biases the estimated effect of education on welfare. A related issue is that the papers often use the education level of an individual such as the most educated in the household or the more educated between the head and spouse as a proxy for household education but do not investigate how the profile of this variable varied across the distribution and what impact it may have on conclusions that can be drawn. For example, if there were strong positive assortative mating trends between the head and spouse in terms of education as we move from the poorer households to richer households (ala Greenwood 2014) with people increasingly marrying those with similar education levels (i.e., better educated marry other better educated) this can bias the coefficient of the variable used to proxy household education. These issues cast doubt upon the validity of the results of previous empirical work. Do the positive impacts of education on household consumption and variations in this impact across the welfare distribution exist even when endogeneity is accounted for? Is assortative mating an issue that influences the conclusions we can draw?

This paper addresses these questions by looking at the effect schooling has had on household welfare in Sri Lanka during the 1990-2006 period. The main contribution of the paper is that the effects measured are corrected for the potential endogeneity of schooling and therefore lends to a more accurate measure of the effect of schooling on household welfare on average and across the welfare distribution. As far as the authors are aware, this is the first paper in the literature

to undertake endogeneity-corrected quantile regression analysis to address this particular issue. The analysis in the paper is also informed by how the profile of the most educated adult in the household, the proxy we use for household education level- changes along the welfare distribution and what implications this has to interpretations of results. The paper uses pooled data from 4 cross section data sets conducted by the Department of Census and Statistics (Household Income Expenditure Surveys) for 1990/91, 1995/6, 2001/2 and 2005/6, pertaining to over 72000 households from across the island[2]. The estimations account for endogeneity of schooling using instrumental variable analysis exploiting the 'Free education policy' implemented in 1945 and the liberalisation of the economy in 1978 that increased substantially employment opportunities within and outside the country (Athukorale and Jayasuriya (1994), Hettige (2005)). The former policy change is expected to have encouraged schooling substantially by reducing costs of schooling while the latter discouraged schooling as it increased the opportunity cost of schooling. To look at variations in the effect of

[2]Data collection is done in twelve equal monthly rounds to capture seasonal variations in income and expenditure. A two stage stratified random sample design is used with urban, rural and estate sectors as the domains for stratification. The primary sampling unit is a census block and the secondary sampling unit is the housing unit within the selected census blocks. The overall quality of the data is good both in terms of response rates and a coverage that that is consistent with other independent surveys carried out on the same population. The datasets focuses on the period before the 30 year conflict in Sri Lanka that ended in 2009 and excludes the North and East of the country where the conflict was based. It is appropriate for the exercise undertaken as the purpose is to look at a reasonably long period of time in recent Sri Lankan history, un-interrupted by structural breaks to the data or major institutional changes (as might be introduced if we included post-war data), allowing for pooling of data to obtain a reasonably large sample size to analyse the effects of education across the welfare distribution.[3] The male proportion ranging from 53-55 per cent in Table 1 is a slight over-estimation because in 16 per cent of the households, the head and spouse are equally educated but it is the head (who is male in 84 per cent of the households) that we take as being the most educated. If we exclude households where the head and spouse are equally educated, the most educated is male in 49 per cent of the households.

education on welfare across rich and poor households we use the uncensored version of the Censored Quantile Instrumental Variable estimator developed by Chernozhukov, Fernandez-Val and Kowalski (2015) that allows estimates to vary across the welfare distribution and accounts for the endogenous relationship between education and household consumption.

The rest of the paper is organised as follows. Section 2 presents the conceptual framework, a descriptive analysis of the profile of the most educated and selected summary statistics. Section 3 discusses the empirical specification while Section 4 discusses the empirical results. Section 5 concludes.

2. Conceptual framework and descriptive statistics

The theoretical model used in this paper is based on Deaton and Muellbauer (1980, 1986), discussed more succinctly in Glewwe (1991). The model itself will not be replicated in this paper and suffice it to note that the basic premise is the standard one of a utility maximising household, subject to constraints. Household utility represents household welfare and as it is unobservable the consequent empirical estimations proxy this by using household consumption. To investigate the effect of schooling on household welfare empirically, one can regress welfare on various explanatory variables assumed to be exogenous or predetermined. This is simply a reduced form estimate of various structural relationships (earnings functions, agricultural production functions, etc.,) which affect welfare.

The Profile of the most educated across the welfare distribution

To answer the question as to what amount of incremental increase in household welfare can be explained by an extra year of schooling, we need to also define whose schooling we consider to matter most to household welfare. The options include an 'aggregate' schooling index based on averaging schooling across adult household members, schooling of the household head, the spouse of the household head or that of the most educated adult member of the household. Jolliffe (2002)

argues that the education level of the most educated is what matters to household income. We use this result in our estimations and use the education level of the most educated adult over 18 years of age, as the education level most relevant to household welfare. In the rest of the paper when we refer to 'education' we refer to that of the highest formally schooled adult of the household, unless specified otherwise.

So who exactly is the 'most educated adult' in our sample of households? In 30 per cent of our sample the household head is the most educated (75% of whom are married and the rest single, divorced, separated or widowed), in 18 per cent it is the spouse of the head, in 15 per cent it is both the head and the spouse as they are equally educated and in the remaining 37 per cent of households it is a person other than the head or spouse such as a child or grandchild who is most educated. In Figure 1 below, we plot the average education levels of the various categories of most educated along the welfare distribution. It illustrates how the category of households where the most educated is neither the household nor head have the highest average education levels increasing along the welfare distribution, followed by households where the spouse is most educated. The group with the lowest education are those heads who are single, widowed, divorced or separated, who are by and large slightly older than the most educated in the other groups.

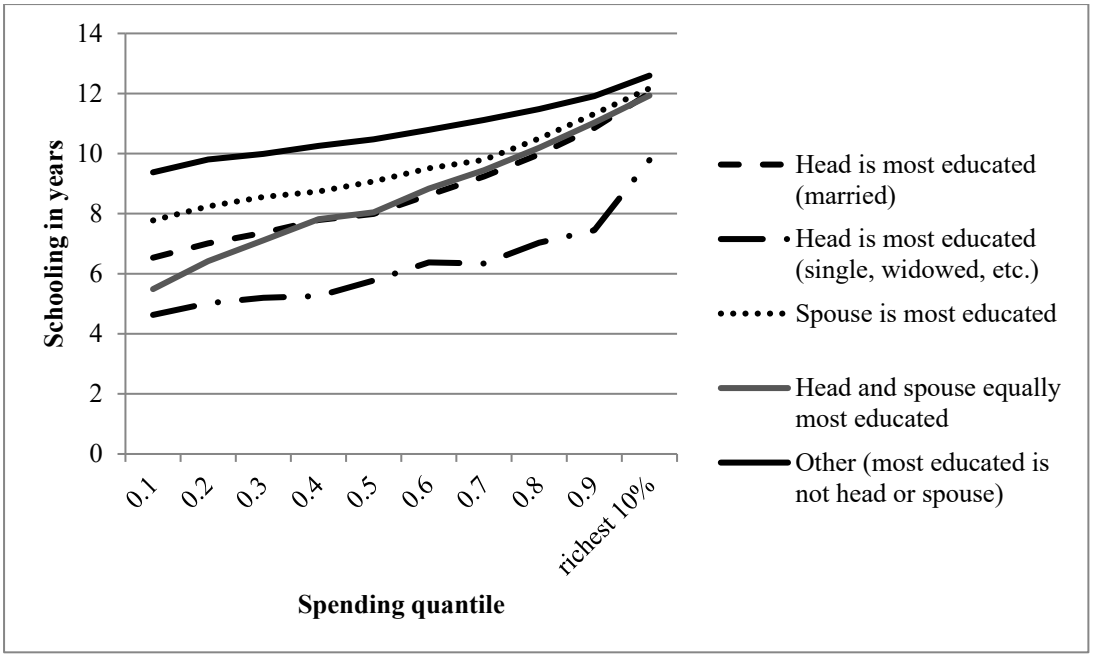

Figure 1: Average schooling of the 'most educated' along the welfare distribution

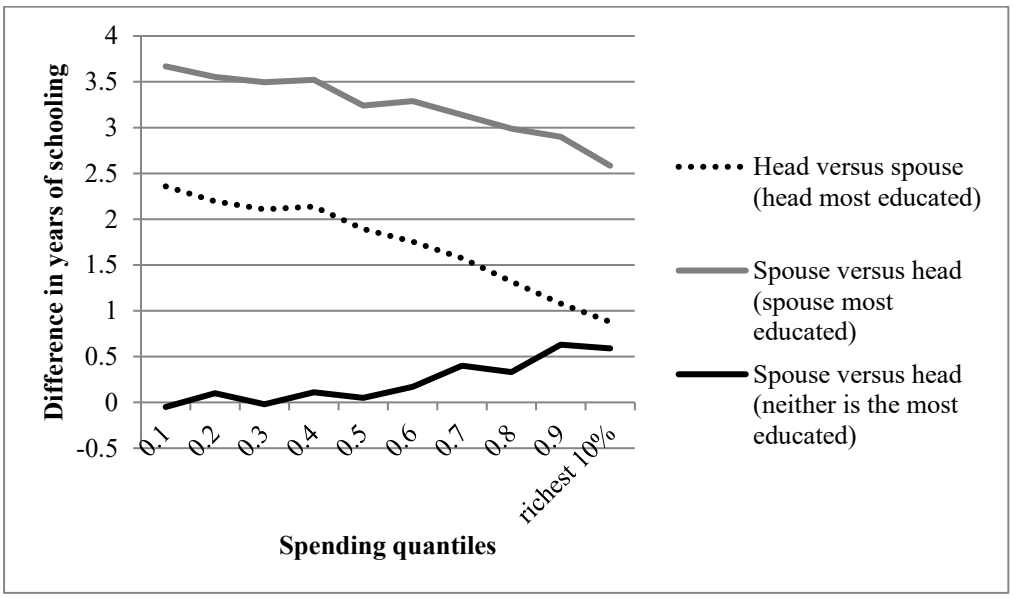

Figure 2: Gap in years of schooling between head and spouse

Further examining the schooling levels of the most educated helps us identify some degree of positive assortative matching in some households progressively increasing as it moves from poorer to richer households. As figure 2 shows, in households where the head (married) is the most educated , the gap in education between the head and spouse progressively reduces from about two

years among the poorest quantiles to about 1 among the richest. Thus the average education of the head versus spouse of 7 versus 4.8 years amongst the poorest quintile becomes 10.8 versus 9.8 among the richest quintile. There is also some evidence of positive assortative matching in households where the spouse is the most educated (. In these households the gap in education between spouses is much wider at all quantiles, at around 3 years on average and the fall in this gap in education across the quantiles is much smaller, around 0.6 years. Thus although mating is progressively more assortative, the bias it may lead to in the education coefficient is probably not as large as the bias if the gap in education was narrower and fell faster. Offering some further evidence of positive assortative mating along the welfare distribution is the fact that households where both the head and spouse are equally educated are twice as common in the richest quartile than the poorest (0.21 versus 0.10, respectively, as proportions), as seen in Table 1. Thus about 57 per cent of our households show some evidence of increased positive assortative mating between the head and spouse across the welfare distribution. But this trend is not supported among households where someone other than the spouse or head is most educated. In these households the gap in education between the head and spouse widens along the welfare distribution starting at - 0.5 among the poorest 10 per cent to about 2/3rd of a year among the richest 20 per cent on average, suggesting negative assortative mating. Thus the education coefficient is affected by both positive and negative elements of assortative mating between the head and the spouse, as far as education levels are concerned, and it is not clear from the descriptive analysis as to which of these effects dominate. Moreover, average education levels of all adults in the household maintains a steady gap compared to the education level of the most educated, along the welfare quantiles (unreported). This suggests that education of all household members is not progressively assortative along the welfare distribution. Thus trends in positive and negative assortative mating among the separate categories of most educated seem to cancel each other out, overall, with no clear evidence of biasing the coefficient on the education variable.

In Table 1 we produce some summary statistics indicating how the identity of the most educated varied across the welfare distribution. The average education of the most educated ranged from 8.08 years to 11.23 years while average age increased from 35 to 40 from the poorest to the richest quartile. But there are variations in these numbers depending on whether the most educated is the head, spouse or someone else. For example, throughout the welfare distribution, the most educated is someone other than the head or spouse in more than a third of the households with the incidence larger among poorer households than the richest, and their age ranges from 26.35 to 28.55 on average along the distribution. In contrast, households where the head (not married) is most educated seem to prevail lesser in poorer quantiles, and the age range of these heads is higher from 50.41 to 53.2.There is almost an equal chance that the most educated is female in houses across the welfare distribution, which is not surprising for Sri Lanka given encouraging rates in gender parity in education and even evidence of higher allocation of household spending towards girls (Himaz 2010)[3]. Household size fell from 5.05 to 3.22 as did the number of dependents aged 0-14 across the distribution from poorest to richest quartile from 33 per cent to 18 per cent. Moreover the proportion living in rural areas fell from 0.84 to 0.62 from the poorest to the richest, reflecting that a higher proportion of richer households were in urban areas. Further analysis of the most educated by gender (unreported) indicates that there are no clear systematic differences between households where a woman is most educated versus a man, based on observable household characteristics. Thus female-most educated households seem randomly distributed as far as key observable household characteristics are concerned with no evidence to support the prevalence of sample selection issues.

[3] The male proportion ranging from 53-55 per cent in Table 1 is a slight over-estimation because in 16 per cent of the households, the head and spouse are equally educated but it is the head (who is male in 84 per cent of the households) that we take as being the most educated. If we exclude households where the head and spouse are equally educated, the most educated is male in 49 per cent of the households.

Table 2 looks at trends in key variables over time. The education level of the most educated improved by about one year from 8.9 in 1990 to 9.8 in 2006. The average age of the most educated increased over this period from 36.1 to 39.4 while the proportion of females who classified as being the most educated increased by 8 per cent such that by 2006, about half the households had a female adult who was the most educated. Average household size and the proportion of dependents aged 0 to 14 years also fell during the period from 4.9 to 4.2 and 0.27 to 0.23, respectively. The data also shows that average spending increased from around Rs. 2458 in 1990 to Rs. 4041 in 2006 and the value of remittances from within the country and overseas have increased considerably in real terms over the 16 years by nearly 8 fold from being around 3 per cent of the value of consumption in 1990 and 13 per cent in 2006. The imputed rented value of the house, if owned, sees the largest change from Rs. 289.61 to Rs. 2280.2.

3. Empirical specification

In the empirical analysis we first look at the influence of education and various other household characteristics, assumed to be exogenous, on household welfare using ordinary least squares estimation (OLS) and quantile regression (QR) analysis. The regression line of an OLS estimation passes though the mean of the sample. In contrast, QR analysis allows us to estimate the effect of education on welfare at different parts of the welfare distribution, making use of the entire distribution. So while OLS looks at effects at the mean, QR analysis can look at effects at other parts of the distribution such as the very poor (lower end of the welfare distribution) and very rich (higher end of the distribution). By looking at the effect of education at various points of the welfare distribution, we can infer to what extent education increases or reduces underlying inequality. The method requires that the spread of education across the welfare distribution is sufficient to conduct the analysis. Although the distribution of education levels is slightly skewed negatively (with median=10, mean=9.48 and skewness=-0.86), there are at least a few of each level in all of the income groups. For example those with post graduate qualification at the poorest level (5 per cent

of the population) is less than 1 per cent of the sample, but not 0. However the corresponding proportion for the poorest 25 per cent is much larger. So in the empirical analysis, our lowest quantile is 0.2.

The basic function estimated for the determinants of household welfare using OLS analysis is

$$y = \alpha + \delta s + \beta X + \varepsilon \qquad (1)$$

where *y* is the logarithm of real per capita monthly household consumption (RPCE) which is used as a proxy for household welfare[4], α is the regression intercept, s represents the years of schooling completed by the most educated adult in the household that can range from 0 to 16 [5]. The vector X contains several other observable control variables that affect household consumption such as age, age squared and gender of the most educated person in the household, household composition (i.e. log of household size and the number of children aged 0 to 14 as a proportion of household members), physical capital and assets (i.e., imputed monthly rental value of house if owned and

[4] The variable is derived by adding monthly household expenditure on food and non-food items and then adjusting it for spatial variations in prices. This figure is then divided by the Gross Domestic Product deflator to convert it to real terms, so that comparisons across the years become meaningful. We then divide it by the number of household members (not including borders, lodgers and servants) to obtain per capita expenditure figures. The base year is set as 2002[4]. The empirical estimation will use the natural logarithm of RPCE.

[5] Completed years correspond to grades completed at school. Grades 1-4 reflect primary education, 5-7, 8-9 reflect early and intermediate secondary education. Completing schooling further for a 10th and 11th year culminates with taking the Ordinary Level examinations. Students can then move on to reading for a further 2 years and take the Advanced Level examinations. Success at this stage can qualify the student to pursue university level education. A 15th year of education indicates completing an undergraduate degree while all further education is coded as 16.

remittances from within the country and abroad)[6] rural/estate sector residence (urban omitted), province of residence (Central, Southern, Eastern, North Central, North Western, Uva and Sabaragamuwa with Western province omitted). The independent error term with mean zero and constant variance is denoted by ε.

In order to account for the possible endogeneity of the education variable *s* we use an instrumental variable identification strategy. We use two instruments. The first is based on Sri Lanka's free education policy that came into force in 1945, which was a set of reforms that made, inter alia, all state education free up to and including university education, established that the instruction has to be in the vernacular language in primary schools and that English be taught as a second language from the third grade. Thus we assign Instrument 1=1 if the most educated in the household was born after 1940 and 0 otherwise[7]. The second instrument is based on the liberalisation of the Sri Lankan economy in 1978 which involved the relaxation of trade and exchange regulations, privatisation and the expansion of the private sector which is argued to have changed the livelihood structure (Hettige 2015) and opened up many opportunities for employment especially for the low and middle income groups. These developments increased the opportunity cost of schooling and are likely to have had a direct effect on the decisions mainly of students still in secondary education (under 18 years of age). Thus the second instrument, Instrument 2=1 if the most educated was born after 1960 and 0 otherwise. Both instruments are as good as randomly assigned as they are based on exogenously imposed reforms. The instruments are both relevant, as they affect the years of schooling pursued: the first positively because education was made free across all schools in the islands and was more accessible as it was to be provided in the vernacular language while the second negatively as it increased the opportunity cost of schooling. The

[6] All monetary variables are adjusted for price differences spatially and temporally, similar to the dependent variable expenditure. The estimations use the logarithm of these values.

[7] The average age of starting school is assumed to be 5 years. Note that until the last two decades, almost all education in Sri Lanka was provided by the government.

instruments also meet the exclusion restriction as they do not affect household consumption in the survey years 1995, 2002 and 2006 directly, but only through the schooling variable. We also assume, reasonably we believe, that there are no 'defiers' in our sample. For instrument 1 these would be individuals who chose to leave school/university or not enter university because the 1945 free education policy was enacted whereas they would have stayed on had it not been enacted. For instrument 2 the defiers would have been those who chose to stay on at school/university or chose to enter university as a result of the 1978 economic liberalisation policy where as they would have not stayed on had it not been enacted. As a relevant and valid instrument, instruments 1 should capture the causal effect of schooling on welfare for the sub-populations of 'compliers' who would have not continued with schooling in the absence of the 1945 reform. Similarly, as a relevant and valid instrument, instrument 2 should capture the causal effect of schooling and welfare for the sub populations of 'compliers' who would have continued schooling in the absence of the 1978 reforms[8].

Although controlling for the quality of education would have been very desirable (Glewwe and Kremer (2006)), there are no suitable variables in the survey for this purpose. Similarly controlling for community characteristics such as the availability of non-farm employment opportunities, proximity to major towns, etc., would have been desirable. However, the lack of consistent data across the five surveys preclude this. It is assumed that the inclusion of regional dummies account for community based differences at least partially. We have also not included ethnicity as an explanatory variable in the analysis, due to incomparability of this variable across the data sets.

[8] In a strict sense, describing the sub populations as 'compliers' and 'defiers' as described in the Angrist, Imbens and Rubin (1996) "local average treatment effect" framework is appropriate when the instrument and treatment (i.e., the endogenous variable) are dichotomous, when the treatment effect is heterogeneous in the population. In our case the treatment is not dichotomous, having values between 0 and 16. The discussion in the text, therefore, informally describes the compliers as the sub population that responds the strongest to the 1945 and 1978 policies, resulting in a first stage that is strongest.

In order to estimate responsiveness of education that addresses the heterogeneity across the welfare distribution, we use quantile regression analysis. When uncorrected for endogeneity, our estimations follow the form

$$\mathrm{Q}_\theta[\mathrm{y}|\mathrm{s},\mathrm{X}] = \alpha_\theta + \delta_\theta s + \beta_\theta X \qquad (2)$$

Where *y* is log RPCE, $\mathrm{Q}_\theta[\mathrm{y}|\mathrm{s},\mathrm{X}]$ is the θth conditional quantile of *y*, α is the regression intercept, *s* denotes years of completed schooling and X is the covariate matrix (excluding s), all following the explanation for equation (1).

However, in order to account for the endogeneity of schooling we use the Censored Quantile Instrumental Variable (CQIV) estimator developed in detail in Chernozhukov (2015) that deals with endogeneity using a control variable approach in the tradition of Hausman (1978). The basic idea as explained in Chernozhukov (2015:212-13) is 'to add a variable to the regression such that, once we condition on this variable, regressors and unobservables become independent. This so-called control variable is usually unobservable and needs to be estimated in a first stage. Our main contribution here is to allow for semi parametric models with infinite dimensional parameters and non-additive unobservables, such as quantile regression and distribution regression, to model and estimate the first stage and back out the control variable'. The two stage *uncensored* quantile regression is a special case of the censored estimator that has been developed, which is used in this paper. Quantile Instrumental Variable (QIV) estimation without censoring follows the parametric version of the CQIV estimator proposed by Lee (2007).

The model can be formalised as follows:

$$Y = \max(Y^*, C) \qquad (3a)$$

$$Y^* = Q_{Y^*}((U|s, X, V) \qquad (3b)$$

$$s = \emptyset(V, X, Z) \qquad (3c)$$

where Y^* is a continuous latent response variable, the observed variable Y is the logarithm of real per capital monthly household consumption obtained by censoring Y^* a continuous latent response variable from below at the level determined by the variable C, where C is lower than the smallest non-zero value of Y; s is the level of schooling attained by the most educated member in the household, X are covariates as described previously, Z are the instrumental variables and V is a latent unobserved regressor called the 'control function,' and U is a Skorohod disturbance that satisfies the independence assumption

$$U \sim U(0,1) \,|s, X, V)$$

The uncensored case, as we use in this paper, is covered by making C arbitrarily small. The functional form of the model estimated is

$$Y^* = \alpha(U)s + X'\beta(U) + \gamma(U)V$$
$$= W'\beta(U), \;\; W = (s, V\; X)$$

where $\alpha(U)$ are the random coefficients of interest.

4. Results

OLS and QR estimation

In this section we present the results for the estimations of the relationship between log real per capita consumption expenditure (RPCE) and household socioeconomic characteristics using OLS,

and at various quantiles of the log RPCE distribution using quantile regression analyses without correcting for the possible endogeneity of schooling.

Table 3, column 1, reports OLS results for selected coefficients[9]. The coefficient on the education variable shows that increasing the schooling of the most educated adult in the household by one extra year corresponds to a statistically significant 7 per cent increase in household welfare, *ceteris paribus*[10]. As the rest of the columns in the tables show, the significant effect of education on household welfare is noticeable at all points of the consumption distribution, ranging from 6-8 per cent. So more education is better for household welfare, with the effect lower at poorer quantiles and higher at richer. Most of the other explanatory variables are also significant in explaining household welfare, with its effect showing some, but not too much variation across spending quantiles.

IV Estimation

We now move onto discussing the results for the estimations accounting for the possible endogeneity. Table 4, below, shows Instrumental variable regression estimation results. In columns 1 and 2, are the first stage and second stage results, with the instruments used being the free education policy in 1945 (instrument 1) and liberalisation of the economy in 1978 (instrument 2).

As the first stage result (Table 4, column 1) shows that the coefficients on these identifying variables are of the expected signs. The first instrument based on the 1948 free education policy is statistically significant at the 1 per cent level, but the second is not. However, the first stage F-

[9] Due to word count constraints full results have not been reported for the regressions in this paper. They are available from the authors on request.

[10] The *ceteris paribus* condition implies that the effect of education on household welfare is while holding other factors constant. One significant 'other factor' is geographical location (or province of residence) as household welfare correlates strongly with location of residence in Sri Lanka. This point holds true for the rest of the results discussed.

statistic rejects the null hypothesis that the coefficients on the instruments are jointly zero at the 1 per cent level, providing evidence of relevance. F(2, 72792) = 52.24 provides support for the contention that there is no weak instruments issue as discussed in Staiger and Stock(1997) and Stock and Yogo (2005). The corresponding second stage results reported in column 2 show that the effect of an extra year of education on welfare is 3.6 per cent (the coefficient on schooling is 0.036 rounded up as 0.04 in Table 3, column 2, to two decimal places), which is much lower than the 7 per cent under OLS estimation. Thus, the OLS estimator over estimates the effect of education on welfare, and is upward-biased, as education also probably picks up unobservables such as ability, motivation and attitudes, inter alia, that lend to household consumption expenditure via earnings, *inter alia.*

When we change the specification of the IV estimation by excluding the non-significant instrument and using just instrument 1 as the identifying variable, we find even stronger results confirming those reported (Table 3, columns 3 and 4): A significant incremental influence of education of welfare of around 3.8 per cent (again rounded up as 0.04 in the table, at two decimal places) significant at the 1 per cent level and the weak instrument bias unlikely to be a problem with first stage coefficient significant at the 1 per cent level and an F statistic of 104.2.

QIV Results

In estimating the model, the first step was to run an OLS regression of s on the instrument Z and exogenous regressors W and obtain a prediction for the control term from the residuals. We ran the QIV regression twice, with the first specification including just the stronger identifying variable (i.e., instrument 1 based on the 1945 free schooling policy) and the second specification including both the identifying variables. As in the case of the IV regressions earlier, the first stage estimations for the QIV are identical to the first stage of the corresponding IV estimations and the previous discussion about the relevance and validity of the instruments hold here as well.

Table 5 reports the final stage results of the QIV estimation where we use just 1 identifying variable. Confidence intervals have been calculated using 100 weighted bootstrap replications[11]. The association between education and household welfare shows a positive relationship prevalent in all quantiles, but the effect is higher in the poorer and middle of the distribution rather than the upper quartiles. At the 20th and 25th quantiles an extra year of education tends to increase real per capital consumption expenditure by 6 and 5 per cent, respectively, while at the median it is around 3.5 per cent. At the 80th it is 3.3 percent and at the 90th it is much less, at 1 per cent.

The result is remarkably different to those from the biased QR estimations that do not correct for endogeneity, that suggest the effect of education is similar or even slightly higher at the upper quartiles than it was at the poorer quartiles. The QIV estimations also show, quite interestingly, that for the 25th percentile and above, the bias is upwards, as reflected in the coefficient for the control terms in the reported final step results, with the upward bias most pronounced at the 80th and 90th percentiles. Thus unobservables such as attitudes, motivation, better quality education and effects of reverse causality between welfare and education are all increasingly overestimating the effect of schooling in years at all quantiles above the 25th with the overestimation being the higher for the higher quantiles. Remarkably, the coefficient on the control term for the lowest quantile in our estimation, the 20th, is negative. This suggests that for this quantile, the OLS estimations were biased downwards. This could mean that for those in the

[11] The bootstrap confidence intervals are not based on standard errors. The QIV code written by Chernozhukov et. al. (2015) does not provide standard errors because the distribution of the estimator is too complicated to calculate the standard error directly. But in terms of inference, the calculated confidence intervals serve the same purpose as standard errors. Thus if a 95% confidence interval includes the null value, the associated coefficient is not statistically significant. If the confidence interval does not include the null value, then the coefficient is statistically significant. The results show that all coefficients on the most educated variable are significant at least at the 90 per cent level (confidence interval estimations areunreported), with the coefficient on the 20th percentile significant at the 95 per cent level (as reported in Tables 5 and 6).

poorest households, the opportunity costs associated with acquiring an extra year of education are high, such that better motivated or the more able leave education to seek employment.

The coefficients on the other unreported control variables in the regressions mostly have expected signs and trends, across the quantiles. For example, rural residence compared to urban exerts a significantly lower effect on household welfare that is higher in richer quantiles. Similarly, residing in any non-Western province compared to the Western province exerts a negative effect. The Western province is the most commercialised and industrialised province of the country. The year dummies indicate that compared to 1990, the years 2002 and 2006 are associated with stronger, positive influences on welfare. The coefficient on the year 1995 is insignificant.

Table 6 displays results for QIV estimation with 2 identifying variables used. The overall results are very similar to those already discussed.

5. Conclusions

This paper investigated the effect schooling has on household welfare by proxying welfare using real per capital consumption expenditure. Household education was proxied by the years of schooling completed by the most educated adult in the family. OLS estimations indicated that an extra year of schooling was associated with a 7 per cent increase in welfare. This result was shown to be an over estimation by the instrumental variable regression that controlled for the endogeneity of schooling. The bias-corrected contribution of an extra year of education on household welfare was estimated to be around 3.8 per cent, on average. The paper also carried out quantile regression analysis allowing for marginal effects on education to vary over the consumption distribution. Estimations not accounting for the endogeneity of schooling showed marginal effects increasing from 6 to around 8 per cent from the poorest to richest quantiles suggesting a stronger effect of education on the welfare of richer households. However, quantile regression estimations accounting for endogeneity, contradict these results, suggesting that the effects of education on welfare are vastly over-estimated especially for households in the top 20 percent of the welfare

distribution. Confirming the instrumental variable results, for households in the middle of the welfare distribution from around the 40th to 75th quantile indicated an incremental effect of education on welfare of around 3.5-4 per cent. The effect was much higher for poorer households at the 20th and 25th percentiles at 6 and 5 per cent, respectively, while the richest households at the 90th quantile saw a much lower effect, at 1 per cent.

The overall result that the endogeneity corrected estimations are lower than the uncorrected ones by about half suggest that unobservables such as ability, motivation, networks, are important for household welfare and that uncorrected estimations are biased upwards, on average. A more detailed, quantile-based investigation indicated that the upward bias on the OLS estimations was evident only for households in the middle and upper end of the distribution. For the poorest 25 per cent of the households, the bias is negative, suggesting that the opportunity costs of spending an extra year in education were high resulting in more able individuals leaving education for employment. This is a finding that requires further investigation. However, the fact that in general, the over-estimation is lesser for poorer households rather than the top 20 per cent of the welfare distribution suggests that the unobservables probably play a much stronger and positive role on welfare in the richer households than others. For example, richer households probably have skills complementing formal education or a better quality education that enables them to earn more in the labour market. These skills could include *inter alia* social and analytical skills, computer literacy or better English language ability that are all vital in a knowledge economy, as well as networks and connections conducive towards improving household welfare and reducing vulnerability that is not captured by schooling levels *per se*. It is also possibility that the effects of endogeneity driven by reverse causality (i.e., welfare levels affecting schooling levels) is more prevalent in the richer part of the welfare distribution leading to a higher bias in the QR results.

It is unclear as to why incremental education has a smaller incremental effect of 1 per cent on overall household welfare of the top 10 per cent, compared to other quantiles. One explanation may lie in the fact that richer households have more members in employment than poorer

households and that these members are likely to have better quality education, complementary skills, network effects and opportunities for rent seeking than their poorer counterparts. Although our limited descriptive analysis in section 2 did not support a clear trend in positive or negative assortative mating by levels of schooling between spouses in the household, it is possible that households in the top-end of the distribution are more positively assorted, in terms of unobservables. This probably results in larger contributions to household welfare (leading to very non-linear wealth distribution). There has been no research conducted in Sri Lanka on these aspects and it remains to be investigated.

An important overall conclusion that is supported from our analysis is that the effects of schooling have been quite positive overall, in terms of contributing to household welfare. The marginal effect of schooling on welfare is significant and positive at all levels of the distribution (holding other factors such as province of residence constant) with a higher effect on the lower and middle quartiles of the welfare distribution. This result is different to findings in the literature that often show that the marginal effect of education on household spending is higher at higher quantiles, when endogeneity effects are uncorrected.

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Table 1: Within-quartile means of selected variables, pooled data 1990-2006

	Expenditure quartile			
	Lowest	Second	Third	Highest
Full Sample				
Real per capita expenditure	1202.72	1888.61	2785.87	6646.40
Schooling of most educated adult (years)	8.08	8.88	9.77	11.23
Proportion of males	0.53	0.54	0.54	0.55
Age	35.26	35.63	37.18	40.7
Household size	5.05	4.35	3.86	3.22
Proportion of children 0-14	0.33	0.26	0.22	0.18
Rural residence (proportion)	0.84	0.81	0.74	0.62
Households where head is the most educated (married)				
Proportion of all households in quartile	0.23	0.22	0.22	0.24
Schooling (of head) in years	7.21	7.78	8.97	11.16
Proportion of males	0.91	0.89	0.85	0.78
Age	43.41	44.14	45.73	47.87
Households where head is the most educated (single, widowed, separated or divorced)				
Proportion of all households in quartile	0.06	0.06	0.08	0.11
Schooling (of head) in years	4.84	5.51	6.43	8.56
Proportion of males	0.23	0.31	0.34	0.38
Age	50.41	51.4	52.75	53.20
Households where spouse of the head is the most educated				
Proportion of all households in quartile	0.21	0.19	0.18	0.16
Schooling (of spouse) in years	8.08	8.86	9.77	11.49
Proportion of males	0.05	0.04	0.05	0.04
Age (spouse)	36.45	37.20	38.81	41.55
Households where the head and spouse have equal levels of schooling and are both the most educated				
Proportion of all households in quartile	0.10	0.11	0.14	0.21
Schooling of head=schooling of spouse	6.13	7.82	9.32	11.28
Age (head)	41.88	41.5	42.37	44.88
Households where the most educated is neither the head nor spouse of head				
Proportion of all households in quartile	0.40	0.41	0.39	0.30
Schooling in years	9.7	10.36	11.02	12.11
Gender	0.51	0.52	0.52	0.52
Age	26.35	26.68	27.41	28.55
Number of households	18204	18203	18204	18203

Table 2: Summary statistics for key variables 1990-2006

	1990/1	1995/6	2002/3	2005/6
Real per capita consumption 2002=100 (Sri Lankan Rupees)	2458.55	2517.13	3600.38	4041.73
Schooling (years) of most educated adult	8.99	9.22	9.86	9.89
Age(most educated adult)	36.1	36.7	37.7	39.4
Gender of most educated adult (proportion of males)	0.57	0.56	0.53	0.49
Household size	4.92	4.56	4.24	4.16
Proportion of 0-14 year olds	0.27	0.26	0.23	0.23
Rural residence (proportion)	.66	.81	.81	.75
Remittances-domestic (real value, Sri Lankan Rupees)	21.17	48.80	102.48	267.7193
Remittances-abroad (real value, Sri Lankan Rupees)	90.39	145.17	230.89	532.3578
Imputed rental value of house (if owned)	289.61	767.7	1386.56	2280.479
Number of households	18204	18203	18203	18203

Table 3 Effect of schooling and other variables on household welfare: Ordinary Least Squares (OLS) and Quantile Regression (QR) estimations

Dependent variable: logarithm of real household per capita consumption expenditure

	OLS	Quantile			
		θ=0.25	θ=0.5	θ=0.75	θ=0.90
	(1)	(2)	(3)	(4)	(5)
Schooling	0.07***	0.06***	0.07***	0.07***	0.08***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.02***	0.01***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Gender (male=1)	0.06***	0.06***	0.05***	0.06***	0.07***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
household size (log)	-0.59***	-0.53***	-0.57***	-0.61***	-0.65***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Rural	-0.18***	-0.14***	-0.17***	-0.19***	-0.22***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Constant	7.48***	7.25***	7.53***	7.78***	8.04***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Observations	72,813	72,813	72,813	72,813	72,813
R-squared	0.45				

Notes: Although unreported, estimations also included the square of age, imputed house value, remittances from abroad and domestically, 7 dummy variables controlling for the different provinces of the country and 3 dummy variables representing the survey years. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of schooling and other variables on household welfare: Instrumental Variable Estimation

	Specification with two identifying variables		Specification with one identifying variable	
	First Stage	Second Stage	First Stage	Second Stage
Schooling		0.04**		0.04**
		(0.02)		(0.02)
Age	0.06***	0.02***	0.06***	0.02***
	(0.01)	(0.00)	(0.01)	(0.00)
Gender (male=1)	-0.15***	0.06***	-0.15***	0.06***
	(0.02)	(0.00)	(0.02)	(0.00)
household size (log)	1.39***	-0.52***	1.39***	-0.52***
	(0.03)	(0.02)	(0.03)	(0.02)
Proportion of 0-14 year olds	-3.20***	-0.21***	-3.21***	-0.21***
	(0.05)	(0.05)	(0.05)	(0.05)
Rural	-0.99***	-0.21***	-0.99***	-0.21***
	(0.02)	(0.02)	(0.02)	(0.17)
Constant	6.76***	7.68***	6.72***	7.65***
	(0.13)	(0.12)	(0.10)	(0.11)
Identifying variables				
Instrument 1 (1945 free education policy)	0.60***		0.62***	
	(0.06)		(0.06)	
Instrument 2 (1978 liberalisation)	-0.02			
	0.54			
Observations		72,813		72,813
R-squared		0.43		0.43
Partial R-squared of excluded instruments:	0.0016		0.0014	
Test of excluded instruments F(2, 72792)	52.24		104.20	
	Prob > F =		Prob > F =	
	0.00		0.00	

Other control variables included the square of age, region and year dummies, imputed house value, remittances from abroad and domestically and the constant term that are not reported. Standard errors in parentheses , *** p<0.01, ** p<0.05, * p<0.1

Table 5 Final Stage QIV Regression Results- Specification 1 (with only 1 identifying variable)

Logarithm of real per capita household consumption expenditure

	p20	p25	p40	p50	p60	p75	p80	p90
schooling (years)	0.06	0.05	0.04	0.03	0.04	0.04	0.03	0.01
lower bound	0.01	-0.02	-0.02	-0.01	-0.02	-0.02	-0.03	-0.07
upper bound	0.11	0.09	0.07	0.08	0.09	0.08	0.09	0.08
Gender (male=1)	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.06
Lower bound	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.04
Upper bound	0.08	0.08	0.06	0.06	0.07	0.07	0.07	0.07
household size (log)	-0.51	-0.5	-0.5	-0.51	-0.54	-0.54	-0.56	-0.55
Lower bound	-0.58	-0.56	-0.54	-0.57	-0.61	-0.62	-0.65	-0.63
Upper bound	-0.44	-0.4	-0.41	-0.44	-0.44	-0.47	-0.48	-0.45
Proportion of 0-14 year olds	-0.1	-0.14	-0.21	-0.21	-0.18	-0.23	-0.24	-0.31
Lower bound	-0.28	-0.37	-0.37	-0.37	-0.35	-0.43	-0.42	-0.53
Upper bound	0.05	-0.04	-0.1	-0.05	-0.03	-0.06	-0.03	-0.09
Rural	-0.13	-0.14	-0.18	-0.19	-0.19	-0.22	-0.24	-0.28
lower bound	-0.2	-0.22	-0.25	-0.24	-0.26	-0.29	-0.29	-0.34
upper bound	-0.08	-0.11	-0.15	-0.15	-0.16	-0.18	-0.17	-0.2
Control Term	-0.004	0.01	0.03	0.03	0.02	0.03	0.04	0.06
lower bound	-0.05	-0.03	-0.01	-0.01	-0.02	-0.01	-0.02	-0.01
upper bound	0.05	0.07	0.09	0.08	0.09	0.09	0.1	0.14

Note: Lower and upper bounds of bias-corrected 95 per cent confidence intervals from 100 bootstrap replications. Other control variables including region and year dummies, age and age squared, imputed house value, remittances from abroad and domestically and the constant term are not reported.

Table 6 Final Stage QIV Regression Results- Specification 2 (with 2 identifying variables)

Logarithm of real per capita household consumption expenditure

	p20	p25	p40	p50	p60	p75	p80	p90
schooling (years)	0.06	0.05	0.03	0.03	0.04	0.04	0.03	0.01
lower bound	0.03	-0.07	-0.04	-0.05	-0.04	-0.06	-0.04	-0.06
upper bound	0.13	0.11	0.12	0.09	0.1	0.09	0.11	0.13
Gender (male=1)	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.06
Lower bound	0.05	0.04	0.04	0.03	0.03	0.03	0.03	0.03
Upper bound	0.07	0.07	0.06	0.06	0.06	0.06	0.07	0.07
household size (log)	-0.5	-0.5	-0.49	-0.51	-0.54	-0.54	-0.55	-0.54
Lower bound	-0.62	-0.59	-0.62	-0.58	-0.61	-0.62	-0.67	-0.73
Upper bound	-0.47	-0.33	-0.39	-0.39	-0.4	-0.41	-0.46	-0.45
Proportion of 0-14 year olds	-0.11	-0.15	-0.22	-0.21	-0.18	-0.23	-0.25	-0.32
Lower bound	-0.2	-0.54	-0.46	-0.49	-0.48	-0.47	-0.47	-0.49
Upper bound	0.13	0.06	0.04	-0.05	-0.01	-0.06	0.02	0.13
Rural	-0.13	-0.14	-0.18	-0.19	-0.19	-0.22	-0.24	-0.29
lower bound	-0.15	-0.25	-0.25	-0.26	-0.27	-0.31	-0.29	-0.35
upper bound	-0.06	-0.09	-0.09	-0.12	-0.14	-0.15	-0.13	-0.15
Control Term	-0.003	0.01	0.03	0.03	0.02	0.03	0.04	0.06
lower bound	-0.07	-0.05	-0.05	-0.03	-0.03	-0.02	-0.04	-0.06
upper bound	0.03	0.13	0.1	0.11	0.11	0.13	0.11	0.14

Note: Lower and upper bounds of bias-corrected 95 per cent confidence intervals from 100 bootstrap replications..Other control variables including region and year dummies, age and age squared, imputed house value, remittances from abroad and domestically and the constant term are not reported.