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Abstract

Using updated Nigeria's micro panel household surveys, we estimate the impact of human capital endowments on household economic well-being – controlling for exogenous circumstance-related factors over which households have little or no control. We found that education and health endowments have significant causal impact on the well-being of the households. More so, education has significant causal impact on the income of households below the bottom 40% (specifically the households at the bottom 25%). Inequalities at the national level are mainly determined by rural-urban and northern-southern inequalities. These observed income inequalities in rural-urban sectors and northern-southern geopolitical zones are mainly propelled by differences in education and health endowments of the households. However, the equalization of human capital endowments in terms of education and health is indeed growth-enhancing. We suggest, therefore, that policies capable of eliminating inequalities in access to schooling and health will enable households at the bottom of the distribution to enjoy better economic well-being.

Keywords: *Poverty, Inequality, Pro-poor growth, Micro panel household data, Nigeria.*

$$\Delta C = C_A - C_B = E(X_s^A)\,(\beta_t^A - \beta_s^A) - E(X_s^B)\,(\beta_t^B - \beta_s^A) \quad (13)$$

$$\Delta I = I_A - I_B = [E(X_t^A) - E(X_s^A)]\,(\beta_t^A - \beta_s^A) - [E(X_t^B) - E(X_s^B)](\beta_t^B - \beta_s^B) \quad (14)$$

Where ΔE is the endowment effect obtained by subtracting the groups' compositional changes over time weighted by their initial coefficients at time s. ΔC is the coefficient effect, referring to the change in income gap due to change in coefficients over time between the groups, given the groups' initial differences in endowments at time *s*. ΔI is the interaction effect, denoting the interaction between the change in endowments and coefficients.

Analyses of growth inclusiveness and its human capital endowment sources

Pro-poor growth rate

Based on the relative pro-poor growth measure recently proposed by Kakwani et al (2010), the current study analyzed growth inclusiveness and its sources in Nigeria. The study used the first and the last wave of the Nigeria panel surveys to analyze pro-poor income growth rate over 2010-2019 period.

Given x to be the mean per capita income of a household, with its function as $f(x)$, the real mean of the population at time t is shown as:

$$\mu_t = \int_0^\infty x f(x)\, dx \quad (15)$$

Following from (15), the growth rate of mean population income between year 2010 and 2019 is expressed as:

$$\tau = \Delta \ln(\mu) \quad (16)$$

In line with Kakwani and pernia (2000), a pro-poor growth reduces inequality, whereas a pro-rich growth increases inequality. Comprehending growth involves examining its distributive pattern. This involves linking growth to income distribution. Hence the need to state a social welfare function, which gives a bigger weight to the utility of the poor, relative to that of the rich. If $u(x)$ is utility function increasing in *x*, then a money metric social welfare function can be stated as:

$$u(x^*) = \int_0^\infty u(x) w(x) f(x) dx \quad (17)$$

Yobe state in the North-East Zone. Other reasons were households refusing to be re-interviewed, no longer traceable, or members had died since Wave 1 (NBS, 2019).

However, in the fourth wave there was a partial refresh of the GHS-Panel sample. The refresh was conducted in order to maintain the integrity and representativeness of the sample. New refresh EAs were selected from the same sampling frame as the original GHS-Panel sample in the wave one period, resulting in a total refresh sample of approximately 3,600 households. In addition, a 'long panel' sample of 1,500 households, designed to be nationally representative, was included to enable continued longitudinal analyses for the sample going back to 2010. In the long-panel sample, about 1,425 households were successfully interviewed, with sample reduction resulting from security issues in the North West zone. Hence, the first, second and the third waves yield a balanced panel of up to 4,407 households with the minimal attrition accounted for, whereas the four waves put together yield an unbalanced panel. From waves one, two and three, we can generate an equivalent sample size of 4,407 households for each of the waves, so that the total number of households in the balanced panel sample for the three waves is 4,407 x 3. In wave four, all the 4,407 sample of same households were not re-interviewed. Hence, there is a long form panel of 1,590 interviewed households in wave one. Out of these 1,590 interviewed households forming a long form panel across wave one, two and three, 1,425 were re-interviewed in wave four. This means the long form panel attrition for the four waves is a minimal 10.4%. Hence, to form a balanced panel for the four waves, we calculate the sample, so that each wave has a total of 1,425 households. Hence, the total number of households in the balanced panel sample for the four waves yields 1425 x 4. It is this balanced panel that we used in the current study. This enabled us to track the updated dynamics of poverty, inequality and growth in Nigeria[2].

Table 1 Continued

Variables	Coefficients, Col. 1	Marginal Effects, Col. 2
Constant	1.3123***	
	(0.0018)	
Sigma_u	0.1549	
	(0.0005)	
Rho	0.0234	
	(0.0002)	
Wald chi2(8)	601060.44	
Prob > chi2	0.0000	
Number of groups	1425	1425
Number of observation	5694	5694

Note: [1]Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Column 2 of Table 1 above reports the marginal effects of the employment model. To ease interpretation in a non-linear setting, we choose the marginal effects over the coefficient estimates. According to the marginal estimates, the household head is 0.59% less likely to find work for a unit increase in the non-self-proportion of employment in a neighbourhood hosting the excluded household. This is not surprising, since a typical scenario in Nigeria is that the employment of members of a given community hosting the household does not directly guarantee that the household head will find work. However, a unit increase in years of schooling of neighbourhood hosting the household leads to 0.003% chances that the household head will find a job. This is expected since a bandwagon effect of schooling is common in Nigeria. Individuals are more propelled to strive to register for schooling when they see their peers consistently going to school. Hence, a rise in years of schooling of the community tends to raise that of the household head, which in turn leads to a rise in their chances of employment.

As in the pooled cross-section work of Mwabu et el (forthcoming), the age of the household head has a decreasing effect on employment. Relative to the male household heads, the female heads are 0.005 less likely to find a job. As expected, household heads living in rural and northern parts of the country are less likely to find a formal job, relative to their urban and southern counterparts. More so, an increase in the proportion of landed properties owned by the community does not guarantee that the house head will find formal employment.

Inverse mills ratio			0.5742***
			(0.0029)
Constant	12.6278***	11.8023***	10.5156***
	(1.7951)	(0.1197)	(0.0113)
F(8,1424)	11.5		
Prob > F	0.0000		
Wald chi2(10,11)		294.28	401546.3
Prob > chi2		0.0000	0.0000
Number of groups	1425	1425	1425
Number of observations	5699	5699	5699

Note: [1]Standard errors are in parentheses. [2]Significance level: *** p<0.01, ** p<0.05, * p<0.1
[3]In the HTIV model, we have used age and land size variables as instruments for education and health respectively.
[4]All regressions were estimated with a household panel spanning 4 waves (2010/11, 2012/13, 2015/16, 2018/19).
[5]Inverse mills ratio is the sample selection term controlling for bias in formal employment. This was generated from our sample selection panel probit model and then included in the panel HTIV regression.

The results in Table 2 (column 3) show that education is positively and significantly correlated with household economic well-being. An additional year of schooling leads to about 0.092 log-points increase in household economic well-being. Improving education would increase household welfare through enhanced occupation. This finding is not only in line with the panel data work of Biyase and Zwane (2017) for South Africa, but also consistent with results obtained in the pooled data works of Baye and Epo (2015) and Mwabu et al (forthcoming) for Cameroon and Kenya respectively. Other key effort-based variables included in the HTIV model in column 3 above are formal sector employment and health status. To identify the effect of health (measured with sickness dummy) on household wellbeing, we instrumented sickness with household land ownership. In line with the literature (Akin et al., 1986; Mwabu, 1986), land size owned by the household is exogenous to its income-generating decisions, and since land is a good proxy for wealth, it is believed to strongly correlate with health status.

Hence, the HTIV model in column 3 of Table 2 corrects for endogeneity and unobserved heterogeneity associated with the health variable (sickness reporting). Households reporting sickness suffered economic well-being decline in the order of about 0.023 log-points relative to those not reporting sickness within the panel periods[3]. This emanates from the fact that chronic ill health is likely to be associated with minimal or no work effort, limited savings/investment, and less motivation for better living standards. Column 3 of Table 2 shows that correcting for sample selectivity bias, securing formal sector employment is associated with 0.007 log-point increase in household economic well-being relative to informal sector workers. Similar to the result in Mwabu et al (forthcoming), this kind of finding, together with the positive education effect, implies that well-educated household heads are more likely, relative to their less educated counterparts, to secure a job in the formal sector.

As already mentioned, the primary results are the national estimates of drivers of poverty in Table 4 above. We have already interpreted them focusing on all covariates. Here, we interpret the drivers of poverty at the zonal level - intentionally focusing on the key variables of the study (marginal estimates in columns 2 and 4 of Table 6). Similar to the results at the rural level in column 2 of Table 5 above, results at the northern level in column 2 of Table 6 show that education years correlates negatively with poverty. However, the reverse seems to be the case in terms of signs at the southern level – as shown in column 4 of Table 6. The southern result is also similar to what we see at the urban level in column 4 of Table 5 above. These results are somewhat expected. We have relatively more households reporting poverty at the northern zone, so that any effort made in terms of additional year of education raises the well-being of the household. However, in the southern zone, most households are already living well, so that an additional year of education does not really add to their already high well-being level. This is similar to what we see for formal employment across northern and southern zones. Formal employment reduces the likelihood that households in the northern zones fall into poverty. However, it is not so for households in the southern zones – suggesting that most households in these zones are already out of poverty. Ill-health reporting does not increase the likelihood that households in the northern zones move into poverty. This is of little surprise since a relatively low number of households have reported ill-health in the northern parts of the country. However, ill-health reporting of household heads in the southern zones increases the chances of households slipping into poverty, specifically by 0.020%.

Impact of human capital endowment on urban-rural and northern-southern poverty gap in Nigeria

Table 4 above reports the national level logit model of drivers of poverty – among other covariates - controlling for the effect of sector and zone on poverty. We can see from this table that the coefficients of sector and zone are significant. This implies the existence of statistically significant rural-urban and northern-southern poverty gaps. In other words, the households in the rural and northern regions are significantly more in poverty than the households in the urban and southern regions. If significant rural-urban and northern-southern gaps exist, further decomposition of it into explanatory components would give more insight into what causes this gap in poverty. In order to achieve this, we use the methods of decomposing inequality in a binary variable into contributing factors – the fairlie non-linear decompositions presented in Table 7 below.

	(0.000)	(0.016)	(0.025)	(0.000)	(0.000)	(0.000)
Total	0.000	-0.065	0.332***	0.000	-0.082	0.248***
	(0.000)	(0.041)	(0.046)	(0.000)	(0.042)	(0.047)
Decomposition %	**Part Two**					
Endowments	0.000	1.693	-1.200	0.000	1.334	-1.627
	(0.000)	(15.228)	(2.230)	(0.000)	(9.239)	(4.015)
Coefficients	0.000	126.036	76.137***	0.000	99.335***	102.362***
	(0.000)	(168.161)	(9.359)	(0.000)	(4.765)	(6.596)
Interaction	0.000	-0.849	-0.583	0.000	-0.669	-0.735
	(0.000)	(9.553)	(4.004)	(0.000)	(7.574)	(6.863)
Random effect	0.000	-26.880	25.646**	0.000	0.000	0.000
	(0.000)	(164.716)	(9.144)	(0.000)	(0.000)	(0.000)
Total	0.000	100.000	100.000	0.000	100.000	100.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note 1Significance: *** p<0.01, ** p<0.05, * p<0.1.
2Age and land size variables serve as instruments in the IV regression for education and health respectively.
3 By default the Kitagawa-Oaxaca-Blinder decomposition reports zeros for the reference year. Hence, 2010/2011 serving as reference year in the decomposition of change show zeros.

The 'decomposition of levels' in column 1 and 2 in part one of Table 10 above also reveals similar results, though differs somewhat in part two. The decomposition results in column 2 (both part one and two) of Table 10 also show a relatively lesser random effect. We focus on these decomposition results since they attempts to deal with the endogeneity problems using the IV approach. The first row showing 'outcome observed' denotes the mean northern-southern differences in log household income, as estimated from the observed data across the panel data periods – 2010-2019. Similar to the increasing trend that we see for the 'outcome observed' for the rural-urban income gap in Table 9, the southern-northern income gap tends to rise over time from 0.134 in 2010/11 to 0.465 log incomes in 2018/19. In terms of the absolute role of endowment, coefficient and interaction, the endowment part, on average contributed a marginal 0.001 log income to the income gap in 2010/11-2018/19. The coefficient contribution to the observed increasing northern-southern income gap is relatively higher, rising from 0.115 log incomes in 2010/11 to 0.367 log incomes in 2018/19. The interaction part contributes 0.004 log incomes to the gap in 2010/2011 and 0.002 log incomes in 2018/19.

We observe a similar trend for the decomposition of change results in the lower part of the Table 10 (column 2) above. We see the change in the northern-southern income gap in comparison to the reference year 2010/11 for the 2015/16 and 2018/19 periods. For the observed outcome, the gap increased between 2010/11 and 2018/19 by 0.332 log incomes. We now look at the effect of changing endowments and coefficients over time. In absolute terms, the changing endowment tends to decrease the gap by some marginal 0.004 log incomes. However, the changing coefficients and interaction increased the gap by 0.253 and 0.014 log incomes respectively.

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