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Simulating policy options for universal child allowances in Ghana

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Abstract: This paper considers the case for universal child allowances in Ghana. It follows findings from an earlier study of 14 middle income countries that examined optimal approaches to reduce child poverty using universal categorical child allowances. The paper describes the demographic profiles that will influence the impact of a universal child allowance: 67 per cent of Ghanaian households contain children, and those households contain 82 per cent of the total population, spreading the impact of a small allowance—funded by a fixed budget—over a very large proportion of the population. Income differences at the margins of the poverty line were found to be small and robustness and sensitivity tests were done to accompany simulation. Simulations found that individual level allowances reduce poverty more than household level allowances. Such individual level allowances weighted to the bottom 40 per cent are found to have better poverty reduction than allowances weighted to young children.

Keywords: poverty, social policy, children, micro-simulation
JEL classification: JEL D31, H53, I32, I38

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1 Introduction

In many high and middle-income countries, children are strongly associated with lower family income: 'Parents are typically in the younger segments of the population, and thus at a relatively low part of their lifetime earnings trajectory; and the arrival of children frequently reduces second earner income. For both reasons, family income tends to be low precisely at the time when demands on that income are high." (Barr 2004: 224). There are also reasons to do with selection, with differential fertility and co-residence patterns operating to link children structurally to households and parents with lower monetary welfare. But such effects at the lower levels of the distribution do not alter the fact that the presence of children can lower household income at all levels of income (and does so across five of our 14 middle income countries because all quintiles of the distribution have lower income if there are children present, controlling for other factors (Evans and Hassen 2018)). The case for considering categorical social protection transfers for groups of the population, so-called demogrants, is strong in such instances—to smooth incomes over the lifetime in a similar way to pensions for old age and retirement. Recent evidence on child poverty in the developing world has pointed to children having higher poverty rates using the international 'extreme poverty' line of US$1.90 per person per day in purchasing power parities, and that these higher poverty rates are robust to equivalence assumptions and to using other monetary poverty lines (Newhouse et al. 2016, 2017). Can universal child allowances adapt to these two aims: (i) lifetime income smoothing; and (ii) poverty reduction?

The primary objective of this paper is to replicate the analysis from an exploratory study of 14 middle income countries in which universal child transfers were simulated in different forms, to assess how far demographic targeting and 'taxing back' allowances from higher income quantiles could improve poverty reduction, while retaining a universal approach (i.e. all children receiving an allowance) (Evans et al. 2018). The findings from that paper found a consistent set of results for all those 14 countries: over-representation of children in the lower quintiles of the income distributions of each country; higher child poverty levels compared to adults; and lower per-capita spending on social protection for households with children compared to others. Simulations of universal child allowances to spend one per cent of GDP were made in response to these findings and these allowances were iterated in different forms to establish which design achieved higher poverty reduction. The findings showed that per-capita allowances (to reflect child population rather than household-level allowances) and 'taxing back' (reducing the level of allowances to the upper 60 per cent of the distribution and using those savings to increase allowances for the bottom 40 per cent) had the largest poverty reduction impacts. Demographic targeting to younger children on its own had very varied effects depending on a country's age distribution and household composition.

How would these findings compare to a similar exercise for Ghana? Rather than simply run a set of model simulations, this paper first considers a range of underlying empirical issues that set the overall constraints for the impacts of universal allowances.

- What is the size of the child population? What is the size and characteristics of the population who live with children and will 'share' the impact of a transfer in their households?
- How are children represented across different types of household and across the income distribution?
- How does the position of the poverty line in the distribution and the size and scale of poverty gaps influence the sensitivity and robustness of simulated transfers?

The paper then turns to consider current profiles of social protection and taxation from the GHAMOD simulation model (Adu-Ababio et al. 2017) and then undertakes four micro-simulations of universal child allowances in similar forms to those undertaken in Evans et al. 2018 (GHAMOD is the tax-benefit microsimulation model for Ghana, which has been developed by UNU-WIDER in cooperation with the University of Ghana, the University of Tampere, and the University of Essex). For a new allocation of government expenditure of 1 per cent of GDP:

- What impact on poverty would paying every household with children an allowance have?
- What impact on poverty would paying every child an allowance have?
- Would poverty impacts improve if households with younger children were prioritized?
- How far would poverty impacts improve if the bottom 40 per cent of households with children received higher allowances than the remainder?

The paper produces two sets of estimates. The main estimates are produced to replicate the assumptions and approach in Evans et al. 2018. A second set of estimates is produced using the GHAMOD default equivalence scale and summary is given in Table 3a.

Data

Replication of Evans et al. 2018 is not possible using direct GHAMOD simulation because the equivalence scale is fixed in the model and cannot be changed to a 'per-capita' basis to replicate their assumptions and results. The simulations in this paper use the output file for 2013 from GHAMOD using the 'GH_2013' simulation that models receipt and liability for a range of existing benefits and taxes.

It is important at the outset to make clear that this paper uses 'net disposable income' as the household welfare measure, and not consumption. This choice is determined by the need to replicate the results from Evans et al. 2018, which used income as the welfare measure from the Luxembourg Income Study (LIS) data, and a harmonized definition of net disposable income lies at the heart of replicating results. However, it is also the case that the arithmetic of static micro-simulation is simpler if income is used, as changes in income from simulated transfers is directly additive to the underlying income-based transfer measure. There would be many more difficulties in translating changes in income to changes in household consumption, and the assumptions of doing so would be potentially large and could influence distributional analysis if elasticities of income to consumption were not constant across the distribution. We return to reflect on these issues later in the paper.

The definition of 'net disposable income' reflects the individual level output variable from the baseline 2013 simulation, '*ils_dispy2*', which, when grossed up to household level and equivalized using a per-capita approach matches the 'per-capita net income' approach in the Evans et al. paper. However, GHAMOD model results are run in addition to ensure that the definition of underlying net disposable income matches that used in GHAMOD and its built-in equivalence scales and to ensure replication of figures for poverty given in Adu-Ababio et al. Doing such a complimentary analysis replicated the GHAMOD poverty headcount of 36.2 per cent based on that different definition of net disposable income alongside other summary statistics given in GHAMOD statistical outputs. The result of this poverty replication is shown in Table 3a. Note that the paper from this point on does not attempt to analysis or simulation using the GHAMOD equivalized income definition nor the Ghanaian national poverty line, nor household consumption in place of income.

In addition to GHAMOD simulated data, micro-data from the source survey Ghana Living Standards Survey (GLSS) 2012–13 was additionally accessed and used to identify the 'primary sampling units' for the source survey data in order to calculate statistical sensitivity and robustness for all profiles and simulations.

2 Demographic targeting and poverty reduction: what are the constraints on simulations in Ghana?

Designing and costing a universal transfer to be paid to everyone of a certain age is often done by simply considering the size of the intended beneficiary population. However, if we want to consider the effects of the transfer on the overall distribution of household welfare and on the effects on the target population, it is wise to consider who else will benefit from the transfer. In our case, children aged 0-17 (age definition matches the definition of children in the Convention on The Rights of the Child (CRC) and to replicate approaches made in Evans et al. 2018) rarely live apart from older adults.

Demographic influences on universal child allowances

Table 1 shows that 46 per cent of the Ghanaian population are children, a total of 12 ¼ million people. The 'working age' population aged 18 to 59 is 47 per cent, and older people aged 60 and over represent a further 7 per cent of the whole Ghanaian population. This simple age-group profile is not intended to capture actual economic activity when describing 'working age', and many children and older people will be 'working', while some of that age will not be economically active. The term 'working age' is thus short-hand for the large and varied population who will include most parents and workers, while the older age group of those 60 and over captures the commonly used assumption for more elderly people in developing countries where life expectancy has not reached the levels that inform pension provision in high income settings. However, if we are to design a transfer that goes to all children, that will be received in households that contain children, and the impact on the income distribution and poverty will be primarily measured by changes to household level incomes as individual incomes are assumed to be shared and aggregated at the household level.

Table 1: Ghanaian population 2013

	%	n 000s
Children (0-17)	46.0%	12,251
0-3	*10.1%*	*2,698*
4-6	*8.2%*	*2,178*
7-11	*13.1%*	*3,495*
12-14	*8.0%*	*2,124*
15-17	*6.6%*	*1,759*
Working Age (18-59)	47.2%	12,587
Older Age (60 and over)	6.8%	1,818
60-74	*4.8%*	*1,266*
75 and older	*2.1%*	*552*
Total	100%	26,655

Note: these populations reflect the weighted survey samples from GLSS6.

Source: Author's calculations using GHAMOD output data GH_2013.

Table 2 shows how the Ghanaian population, and Ghanaian children, co-reside. Households are shown by their age-group composition. Households with children are divided into those that solely comprise of children, and those that have children living with working age and older adults in differing combinations. Most children (78.5 per cent), and the majority of the population (78.5 per cent), live in 'two generation' households comprised of children and working age adults that are 53.3 per cent of all households. Three generation households are a further 11.9 per cent of all households that contain 19 per cent of children and 19 per cent of the total population co-residing in households with children, working age and older people. Other types of households are much rarer, with so-called 'missing generation'[1] households that contain just older people and children are 2.3 per cent of households that contain 1.9 per cent of the population and 2.3 per cent of children. 'Child only' households are very rare indeed and the survey sample of them is too small to report accurate proportions but are at the margins of 0.1 to 0.3 per cent of population totals. One of the most important findings is that children are more widely spread than their 46 per cent representation of the population would suggest: they live in two thirds of all households (67.6 per cent) which represent nearly nine tenths (87 per cent) of the whole population. Any universal allowance will thus be very widely spread indeed when it comes to influencing overall incomes and poverty.

Table 2: Co-residence and household age composition of population: Ghana 2013

	Households		Population		Children	
	%	n 000	%	n 000	%	n 000
Households with Children						
children only	0.1%	*7*	*0.03%*	*8*	*0.07%*	*8*
children and working age	53.3%	3,515	66.1%	17,619	78.5%	9,620
children and older age	2.3%	153	1.9%	493	2.4%	290
children, working age and older age	11.9%	785	19.0%	5,057	19.0%	2,331
sub-total	67.6%	4,453	87.0%	23,177	100.0%	12,250
Households without Children						
older Age only	4.8%	316	1.5%	392		
older and working age	3.8%	248	2.8%	746		
working age only	23.9%	1578	8.8%	2,338		
Total	100%	6,601	100%	26,655		

Note: these populations reflect the weighted survey samples from GLSS6.

Source: Author's calculations using GHAMOD output data GH_2013.

When we consider this in terms of age-based targeting, we can see that there are two groups: those that are *directly targeted* by the universal age-assumption (everyone in that age group gets a transfer) and the *indirectly targeted* age groups that will 'share' the benefits of that transfer through co-residence. Profiling solely by individual age-group will miss this, relying on just two-dimensional population totals rather than a three-dimensional co-resident profile that considers how the population live together in households. Figure 1 shows an example of an approach that appreciates such a household co-resident population approach:

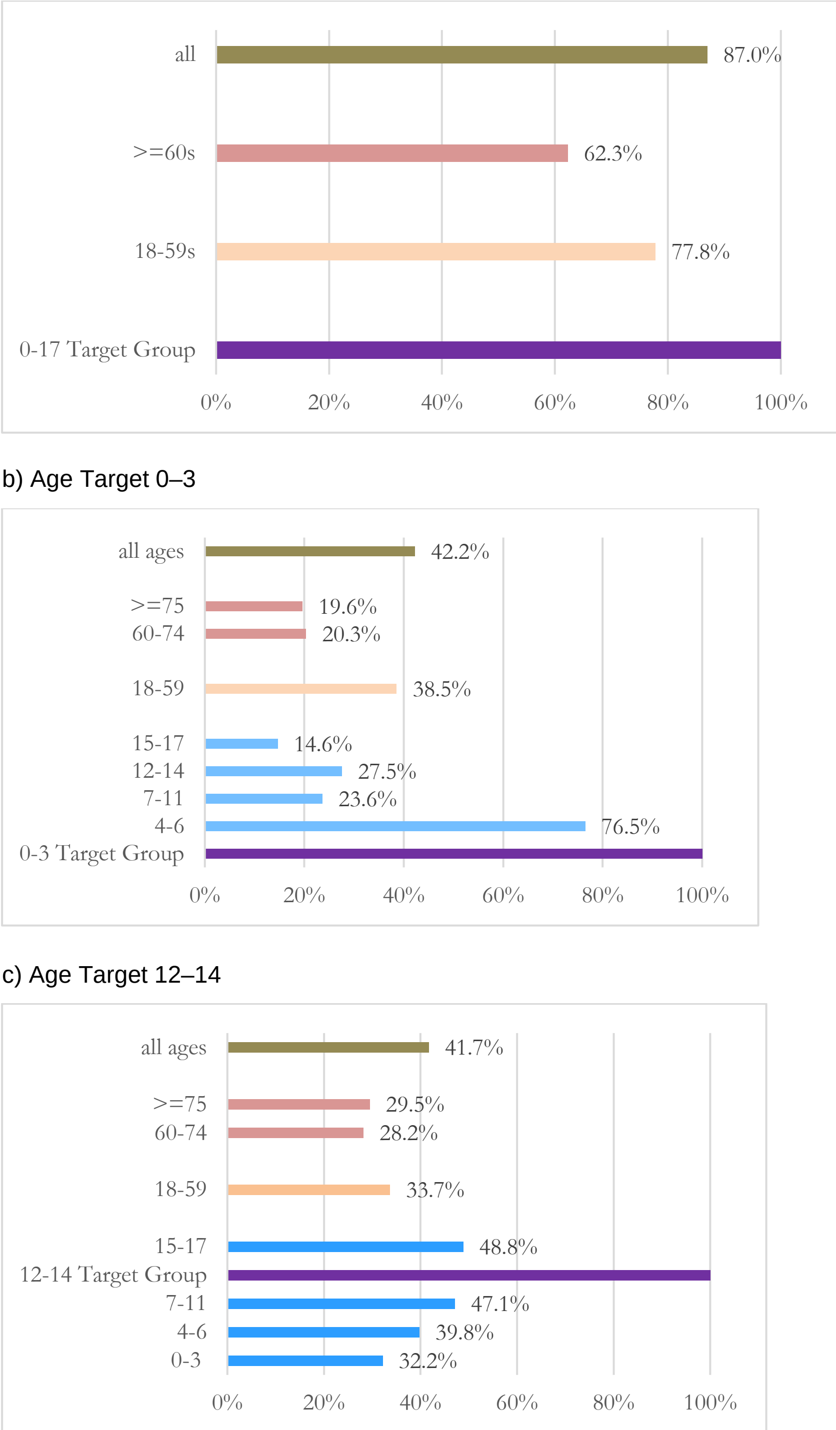
[1] Of course, these households may not reflect 'missing' parents at all but may reflect the fact that older men and women have had children when they were aged 42 or over.

Figure 1: Direct and indirect targeting for universal child allowance in Ghana by age

a) Age Target 0–17

b) Age Target 0–3

c) Age Target 12–14



Note: these populations reflect the weighted survey samples from GLSS6.

Source: Author's calculations using GHAMOD output data GH_2013.

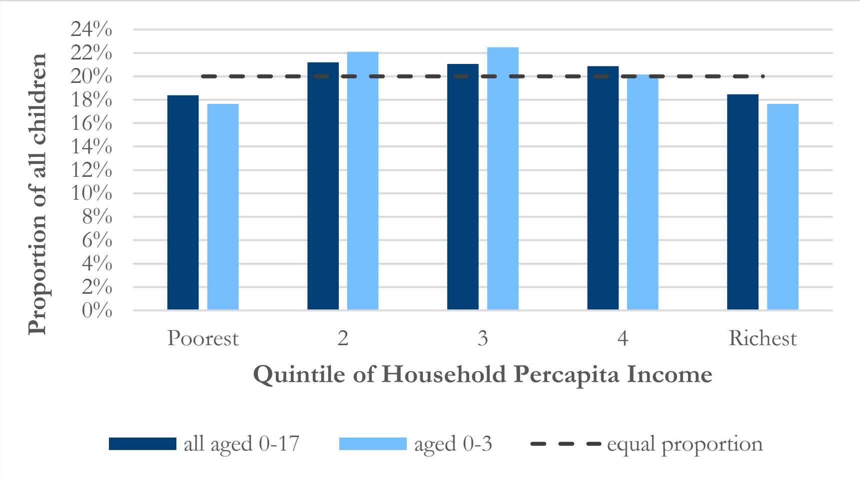
A universal allowance for all ages of children (0-17) (shown in purple in Figure 1) would additionally indirectly affect 77.8 per cent of all working age (shown in green), and 62.2 per cent of older people (shown in orange). A total of 87 per cent of the population (shown in grey). A universal allowance solely for infants aged 0-3 years old (purple) would additionally indirectly affect older children (76.5 per cent of 4-6-year olds, 23.6 per cent of 7-11-year olds, 27.5 per cent of 12-

14-year olds, and 14.6 per cent of 15-17-year olds; all shown in blue); and 38.5 per cent of working age and around 20 per cent of older adults. A total of 42.2 per cent of the population would benefit from such an allowance. A universal allowance targeting older children aged 12-14 would additionally indirectly reach other ages of children (32.3 per cent of 0-3-year olds, 39.8 per cent of 4-6-year olds, 47.1 per cent of 7-11-year olds, and 48.8 per cent of 15-17-year olds); and 33.7 per cent of all working age and 28-29 per cent of all older people. A total of 41.7 per cent of the population would benefit from such an allowance.

Children in the income distribution

Knowing who children live with is one element of designing a universal child allowance and having ex-ante evidence of its direct and indirect effects on household welfare. Another crucial element is knowing where children are in the overall distribution. Figure 2 shows the distribution of the total Ghanaian child population across quintiles of household disposable income (using the per-capita equivalence assumption, see Annex 1 for GHAMOD equivalence results).

Figure 2: Distribution of children by income quintile

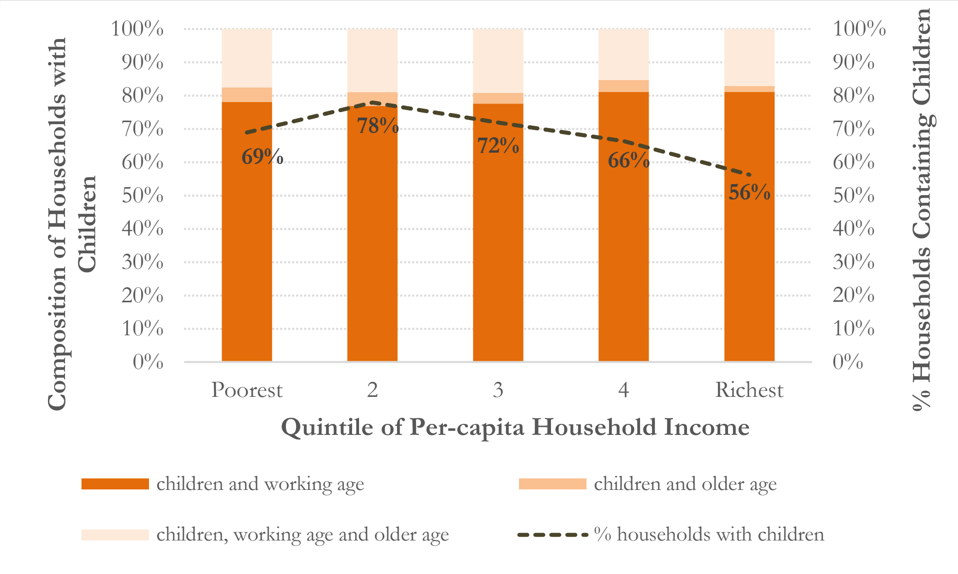


Source: Author's calculations using GHAMOD output data GH_2013.

Figure 2 shows that children are under-represented in the poorest and richest quintiles of household net per-capita income, while over-represented in the middle three quintiles of the distribution. The youngest children are similarly distributed but are slightly more under and over-represented at the ends and middle of the distribution respectively. This profile differs from those of the 14 countries in the Evans et al. paper, where children were consistently over-represented in the bottom 2 quintiles in all those countries.

Figure 3 shows how household composition for households with children differs across the same quintiles. We see on the right-hand scale (black dashed line) that the quintile with the highest proportion of households with children (78 per cent) is the 2nd quintile, which influences poverty results that are based on a poverty line at the margins of the poorest decile (69 per cent) and 2nd decile (see poverty discussion below). The proportion of households with children declines consistently across he 3rd, 4th and richest quintiles, but still the majority (56 per cent) of households in the richest households contain children. In terms of age composition of households (left hand scale and green stacked bars), we see very little difference overall but higher proportions of households with children and elderly people in the lower three quintiles, and thus higher proportions of two generation (working age and children) households in the 4th and richest quintile.

Figure 3: Household composition of households with children by quintile

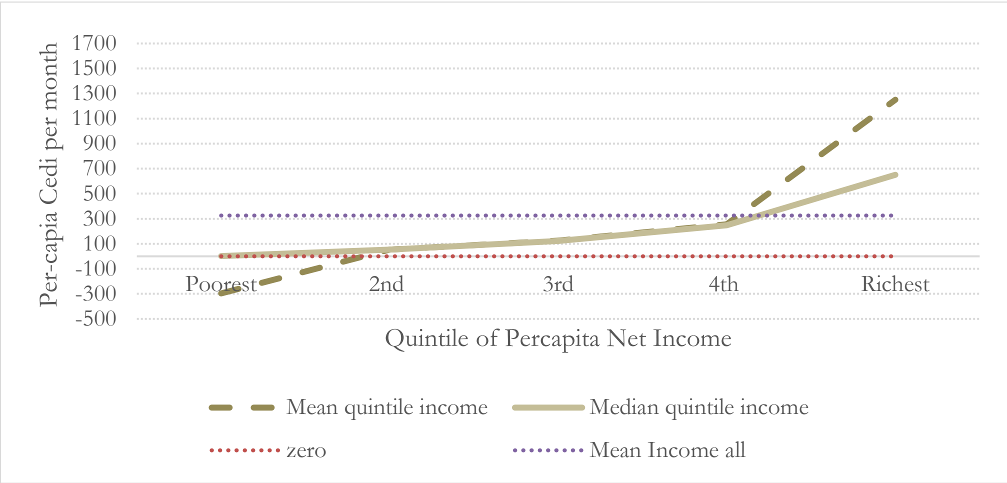


Source: Author's calculations using GHAMOD output data GH_2013.

Poverty and the income distribution

The overall income distribution will have a large influence on how universal transfers affect household welfare and can lift poor households out of poverty. The use of 'net disposable income' as the welfare metric in GHAMOD (version 1.1) produces a large number of negative incomes, even after negative incomes from self-employment are set to zero. The overall income distribution is very skewed indeed with long upper and lower tails. Figure 4 gives an overview of median and mean incomes by quintile and illustrates how far the lower and upper tails of the overall distribution pull apart. At the bottom of the distribution, and key to poverty profiling and to assessing the impact of transfers on poverty reduction, we see that incomes in the poorest quintile are negative on average (-296 Cedi per-capita per month but have a median value of positive 2 Cedi) with large negative incomes at the tail dragging down the mean value. Over the 2nd, 3rd and 4th quintiles, mean and median incomes for each quintile are close in value, but are dragged apart again by the upper tail that makes the mean income for the richest quintile 1.9 times the value of the median.

Figure 4: Median and mean per-capita net disposable income by quintile

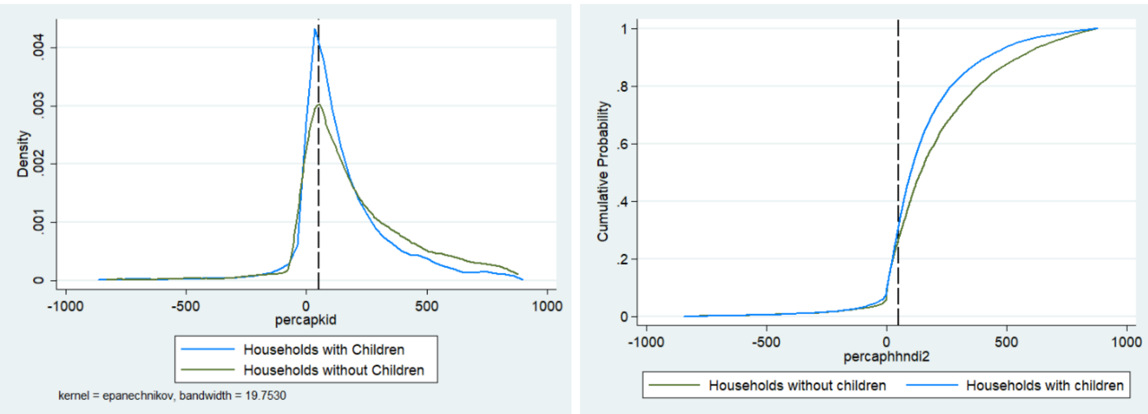


Source: Author's calculations using GHAMOD output data GH_2013.

To show these distributions graphically as kernel density and cumulative density functions, needs a considerable level of trimming of data to produce visually interpretable results[2]. Figure 5 shows the distributions of income for households with and without children with such trims to the upper and lower tails. The dashed vertical black line shows the poverty line using 50 per cent of median per-capita net disposable income (discussed below).

Figure 5: The distribution of net disposable income for households with and without children

Kernel Density | Cumulative Density



Source: Author's calculations using GHAMOD output data GH_2013.

Figure 5 suggests that the overall distributions of net disposable per-capita income for households with (67.6 per cent of all households) and without children (32.4 per cent) differ little at income levels at the margins of the poverty line for those below that line. The kernel density functions show the poverty line cutting the distribution at similar points in the densest part of both distributions, and the cumulative density function show that households with children dominate (are poorer) only for income levels above the poverty line. But these profiles suggest that the poor and those at the margins of poverty are not easily distinguishable between households with and without children. Figure 5 also points to an underlying measurement problem of sensitivity at the

2 I explored transformation of the data to produce improved graphical representation but was faced with the problem that log transformation dropped all negative values, and that alternative transformations were either overly complex and difficult to interpret or produced dubious results.

margins of the poverty threshold. Very small differences in income can make apparently large proportional changes in poverty headcount as the poverty line cuts the distribution at the densest part of the distribution where values for household income are not very different in absolute terms. This problem is potentially a serious one when we come to consider the overall effect of simulated transfers on reducing the poverty headcount.

Poverty and child poverty

The World Bank reports rapid poverty decline in Ghana using the National Poverty Line: from 52.6 per cent in 1991, to 31.9 per cent in 2005 and to 24.2 per cent in 2012 (Molini and Paci 2015). The 2012/13 national poverty estimates from GSS6 use a *household consumption aggregate* as a welfare measure and not disposable income. These give a 24.2 per cent headcount for 'all population' poverty (GSS 2014). There are two major caveats that follow. First, that the definition of 'net disposable income' at household level may not be the same as that used in Luxembourg Income Study in Evans et al. This is not foreseen as a large problem as both approaches calculate gross incomes from a range of sources and reduce these by direct taxes and social security contributions. Determining whether these calculations are 100 per cent consistent at the national level and capture all forms of income and direct taxation across all 14 countries used in LIS and for Ghana, is beyond the remit of this paper. The second and more intractable problem is how consumption and income-based estimates can be reconciled for Ghana. Given that national Ghanaian poverty estimates are calculated using household consumption, the direct policy implications of calculations using income could be less useful. For instance, due to the different distributions that are created (in particular the 7.8 per cent of households with negative incomes), different levels of poverty arise even when using a constant value poverty line (Adu-Ababio et al 2017). Reconciling household consumption welfare measure to one based on income would require a close consideration of the computation and composition of both welfare aggregates: do they contain imputed resources such as rents from homes and durables; do they deduct non consumption expenditures consistently – such as payments to savings or debt, or payments of informal transfers or informal taxes (e.g. payments of Zaqat could be a significant factor for Muslim populations); are they adjusted from geographic price differences, for instance?

The calculations for these simulations use per-capita net disposable income and poverty defined in relative terms as 50 per cent of median per-capita income in order to replicate the approach in Evans et al. This leads to an estimate for poverty headcount at 26.3 per cent as shown in Table 3. This is two percentage points higher than the national poverty estimate using consumption and the national poverty line, but 10 percentage points lower than the GHAMOD estimates using net disposable income using the Ghanaian equivalence assumption, see Table 3a and Adu-Ababio et al. 2017. Given the inherent sensitivity of poverty estimates due to the location of the poverty line in the overall distribution and the presence of clustered values for welfare at the margins of the poverty line; and in recognition that estimates are based on survey data with sampling and measurement error, 95 per cent confidence intervals (c.is) are reported for all poverty headcount estimates alongside standard errors. Such bounds of confidence suggest that the per-capita estimates for headcount rates using per-capita net income are close to the national poverty line at the lower bound.

Table 3 also shows disaggregated headcount poverty rates for different age groups: focusing on children. To calculate poverty at the individual level for different age-groups I follow the methodology of the World Bank, Eurostat and OECD: the poverty rate is the number of individuals in that age-group who are poor as a percentage of the national population of that age-group. Child poverty for the whole 0-17 age group is higher, 27.2 per cent, than for the whole population and higher than working age adult poverty at 24.2 per cent. These profiles do not have overlapping c.is and can be considered different in first order terms. Table 3 shows that child poverty rates differ by age but by levels that are mostly within the bounds of the overall estimate for children of all ages. Older people, and particularly those aged 75 and over, have the highest poverty rates.

Table 3: Poverty headcount estimates

Per-capita NDI	% poor	*95% confidence intervals*	
All Population			
Per-capita NDI	**26.3**	*24.8*	*27.7*
(standard error)			
All Children aged 0-17 (n=33,955)			
Per-capita NDI	**27.5**	*25.9*	*29.1*
(standard error)	0.0082		
Children aged 0-3 (n=7,505)			
Per-capita NDI	**27.5**	*25.5*	*29.4*
(standard error)	0.0101		
Children aged 4-6 (n=6,148)			
Per-capita NDI	**27.9**	*26.0*	*29.9*
(standard error)	0.0101		
Children aged 7-11 (n= 11,807)			
Per-capita NDI	**28.3**	*26.4*	*30.2*
(standard error)	0.0096		
Children aged 12-14 (n= 7,580)			
Per-capita NDI	**27.4**	*25.4*	*29.5*
(standard error)	0.0098		
Children aged 15-17 (n= 4,850)			
Per-capita NDI	**27.2**	*25.1*	*29.2*
(standard error)	0.0104		
Adults aged 18-59 (n=33,188)			
Per-capita NDI	**24.7**	*23.3*	*26.2*
(standard error)	0.0073		

Older Adults aged 60 and over (n=5,229)			
Per-capita NDI	**28.3**	26.2	30.5
(standard error)	0.0108		
Older Adults aged 60-74 (n=3,628)			
Per-capita NDI	**26.8**	*24.6*	*29.1*
(standard error)	0.0115		
Older Adults aged 75 and over (n=1,601)			
Per-capita NDI	**31.9**	28.6	35.2
(standard error)	0.0168		

Source: Author's calculations using GHAMOD output data GH_2013.

Table 3a shows the same set of results for the 'inbuilt' GHAMOD definition of net disposable income that uses the national definitions and equivalence scales. Much higher poverty rates, far above those found using consumption, are seen using the same nominal poverty line.

Table 3a: Poverty profiles using GHAMOD income definition and equivalence scale

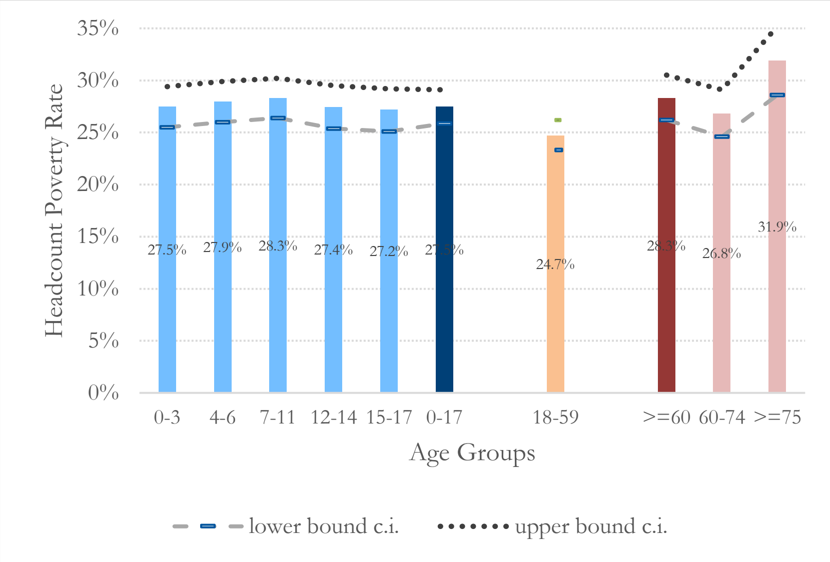
National Poverty line (Calorific Equivalence Scale and Cedi 109.5 pcm)		
% poor (standard errors)	***95% confidence intervals***	
All Population (n=72,372)		
36.2	*34.5*	*37.8*
0.0081		
Children aged 0-17 (n=33,955)		
37.9	*36.1*	*39.7*
0.0092		
Children aged 0-3 (n=7,505)		
36.4	*34.3*	*38.5*
0.0110		
Children aged 4-6 (n=6,148)		
37.9	*35.7*	*40.2*
0.0114		

Children aged 7-11 (n= 11,807)		
38.7 0.0105	*36.5*	*40.9*
Children aged 12-14 (n= 7,580)		
38.3 0.0115	*36.0*	*40.5*
Children aged 15-17 (n= 4,850)		
38.1 0.0119	*35.8*	*40.4*
Adults aged 18-59 (n=33,188)		
34.1 0.0083	*32.5*	*35.8*
Older Adults aged 60 and over (n=5,229)		
38.3 0.0118	*36.0*	*40.6*
Older Adults aged 60-74 (n=3,628)		
36.9 0.0128	*34.4*	*39.4*
Older Adults aged 75 and over (n=1,601)		
41.6 0.0176	*38.2*	*45.1*

Source: Author's calculations using GHAMOD output data GH_2013.

Note that from this point on, this paper only takes forward the per-capita net disposable income definition and original results from Table 3. Figure 6 gives a graphical summary of Table 3 and enables a visual 'eye-balling' of the age-disaggregated point values for poverty headcount rates alongside their bounds.

Figure 6: Poverty headcounts by age



Source: Author's calculations using GHAMOD output data GH_2013.

Poverty reduction and transfers

Before undertaking simulations, it is worth considering how transfers will affect poverty headcount rates using these data and welfare definitions. In the simulations and in the reporting of poverty prevalence, I do not report poverty gaps. This is because the presence of large proportions of households with negative incomes among the poor make the computation of 'average gaps' difficult to interpret. The presence of these negative incomes will limit what can be modelled as poverty reduction when simulating transfers and is likely to have different outcomes from simulations that use consumption-based welfare measures that do not have negative values for the poor population. Any poverty reducing simulated transfer has to give poor households additional income to take them over the poverty line, but those with negative incomes will be too far below poverty to be affected by anything other than a huge transfer in absolute terms. As a universal transfer, by definition, will not be a huge transfer as it is given to the whole population of a certain age rather than being selectively targeted to reflect the level of monetary welfare of the poor households.

Table 4 shows the poverty gaps calculated for per-capita incomes by dividing the poor population into 4 quartiles alongside values for the mean and median poverty gap. The mean poverty gap is huge, 5.3 times the value of the poverty line, while the median is 71 per cent of the poverty line. When we consider the quartile groups of poor by their poverty gap – we see that the 20 per cent of poor who are closest to the poverty line have a gap of 18 per cent and this is important context for any universal transfer that have a poverty reducing effect only for those closest to the poverty line.

Table 4:Poverty gaps for per-capita disposable income

	Normalised Poverty Gap (% of poverty line)	95% c.i.s	
All Poor Population (26.3%)			
Median	0.71		
Mean	5.3	*4.0*	*6.5*
Mean Gap for each Quartile of Poor			
closest to poverty line	0.18	*0.17*	*0.19*
2nd closest	0.53	*0.52*	*0.54*
3rd closest	0.90	*0.89*	*0.91*
deepest in poverty	17.45	*13.01*	*21.90*
EQIVALISED			
All Poor Population (36.2% poor)			
Median	0.66		
Mean	2.7	*2.1*	*3.3*
Mean Gap for each Quartile of Poor			
closest to poverty line	0.18	*0.17*	*0.19*
2nd closest	0.50	*0.49*	*0.51*
3rd closest	0.81	*0.80*	*0.82*
deepest in poverty	8.54	*6.40*	*10.67*

Source: Author's calculations using GHAMOD output data GH_2013

Simulating universal transfers based on a fixed budget will result in transfers with a low absolute monetary value: the budget is spread over a large population. Such small transfer levels will potentially make small differences to the incomes of poor and result in changes to poverty headcount could well be within the bounds of 95 per cent confidence intervals shown in Table 3 and Figure 6. This suggests an underlying measurement problem that is worth considering in advance of any simulation: what is the statistical significance of reducing poverty headcounts when small increases of income may affect small numbers of poor people and produce small differences in poverty levels?

Table 5 shows the difference in poverty rates for the whole population based on simulated transfers set to 5, 10 and 15 per cent of the poverty line value. While each simulated transfer only reduces headcount poverty by less than one percentage point, each new simulated poverty rate is statistically different from the baseline, when z-tests are used to test the level of difference. A reduction in the baseline poverty rate of just 0.3 per cent from the transfer valued at 5 per cent of the poverty line is a statistically significant difference after the z-test. This ability to derive significant difference for small incremental changes in poverty rate results from the large sample and associated small standard errors. Any simulation considering poverty rates for smaller samples of the population, for instance for children of specific age groups, then z-tests would be appropriate to test for differences in poverty rates from the simulations reporting small samples for such sub-groups of the population.

Table 5: Significance of poverty rate from different levels of transfer

(n=72,372)	**poverty rate**	lower bound c.i.	upper bound c.i.	z value	*Pr(Z > z)*
Original Pre-transfer	**26.3%**	*24.8%*	*27.7%*	--	--
standard error	(0.0073)				
With Transfer @ 5% of PL	**26.0%**	*24.6%*	*27.5%*	*- 12.30*	1.0
standard error	(0.0073)				
With Transfer @ 10% of PL	**25.8%**	*24.4%*	*27.3%*	*- 17.90*	1.0
standard error	(0.0073)				
With Transfer @ 15% of PL	**25.6%**	*24.2%*	*27.1%*	*- 21.40*	1.0
standard error	(0.0073)				

Source: Author's calculations using GHAMOD output data GH_2013.

But these statistically significant differences in poverty are driven by small changes in income. Table 6 shows what is driving these different simulated poverty rates by considering income difference at the margins of poverty reduction; i.e. for the population who are originally poor but who cross the poverty line when given the simulated transfers shown in Table 5. The changes in income that drive poverty reduction are very small indeed. In the case of the transfer valued at 5 per cent of the poverty line, the 3 per cent reduction in poverty shown in Table 5 results from just 151 observations in the data who have incomes that change on average from being 1.1 per cent below the poverty line to just 0.8 per cent above it, a change in per-capita income of 0.9 Cedi. The underlying change in income that drives poverty reduction is negatively significant, as the t-test shows that the difference between the baseline and simulated income using *p*-values is less than zero. While increasing the level of transfer means that larger samples of poor are lifted over the poverty line and that the resulting income differences are larger on average for the poverty leavers, the t-tests continue to show robust negative difference – that the differences in income that drive poverty reduction for transfers set at 10 and 15 per cent of the poverty line remain small in nominal terms, (1.9 and 2.7 per-capita Cedi per month), and have *p*-values of less than zero.

Table 6: Significance of simulated income differences at the margins of poverty reduction

Poverty Leavers	Pre-transfer income (normalised to poverty line)		Post transfer income (normalised to poverty line)		t-test of difference t	P < or > 0
Transfer 5% of PL						
n= 151	**98.9%**		**100.8%**			mean(diff) < 0
standard errors	0.0648		0.0452			
mean per cap Cedi pcm	49.8		50.7		16.21	Pr(T < t) = 1.0
95% c.i.s	0.987	0.992	1.006	1.010		
Transfer of 10% of PL						
n=319	**98.2%**		**101.6%**			
standard errors	0.0839		0.0837		23.11	mean(diff) < 0
mean per cap Cedi pcm	49.3		51.2			Pr(T < t) = 1.0
95% c.i.s	0.979	0.985	1.013	1.020		
Transfer of 15% of PL						
n=455	**97.4%**		**102.7%**			
standard errors	0.1083		0.1228		28.09	mean(diff) < 0
mean per cap Cedi pcm	49.0		51.7			
95% c.i.s	0.969	0.978	1.022	1.032		Pr(T < t) = 1.0

Note: standard errors calculated on underlying monetary values.

Source: Author's calculations using GHAMOD output data GH_2013.

The results from these tests suggest that it is important to be able to show the results from significance tests as part of simulations, and I use this approach in the simulations in Part 3 below and report them in Annex 1. The practical importance of doing this must be emphasized alongside the technical aspects of statistical interpretation. Any simulation that will be used for policy discussion should be wary of flagging the poverty change at the expense of also interpreting income change and policy makers should be made aware of the uncertainty of measuring income differences at the margins of poverty when reporting modelled tax-benefit simulations.

Recap

This second section of the paper has explored general issues that will affect and determine simulations of universal child allowances. It has shown that:

- simple population counts will poorly prepare simulations for the effects of allowances that are shared by those who live with children: a universal allowance in Ghana will go to 46 per cent of the population who are children, but simultaneously increase the incomes of 67 per cent of all households, in which 87 per cent of the population live.
- Ghanaian children are not over-represented in the bottom quintile of the distribution, although child poverty rates are 27.5 per cent compared to working age adult rates of 24.7 per cent. However, the overall distribution of income shows that households with and without children are very difficult to distinguish for those who are poor or at the margins of poverty.
- Simulating the effects of a universal transfer of a small nominal value will face problems of interpretation due to the position of the poverty line in the densest part of the overall distribution, where small differences in income can result in larger differences in poverty

prevalence. This means that statistical uncertainty results from simulations and testing for 'difference' is recommended.

3 Simulating options for universal child allowances in Ghana

The remaining parts of the paper replicate the simulations of universal child allowances that were made across 14 middle income countries by Evans et al., op-cit.

The first part of the simulation is to establish a fixed budget for all variants of allowances that will be modelled. Following Evans et al. (2018), this budget is fixed and set at 1 per cent of Ghanaian GDP in 2013.

Table 7 shows the funding and per-capita assumptions for the simulation of universal child allowances. GDP was 93.4 billion Cedi in 2013, and 1 per cent is thus 934 million Cedi. There is a choice in establishing the number of households with children and without children–either using Census and population projections, or the GSS6 survey data with survey weights to give survey-based populations from the same source as the income data. Such population figures provide the denominators to calculate allowance rates. Using weighted survey data, Table 7 shows that a household level allowance to all 4.46 million households with children would give an annual transfer of 209 Cedi, while an individual level allowance to each of 12,25 million children would provide 76 Cedi per annum.

Table 7: Budget assumptions for universal child allowances

Parameters	Population	Annual Amounts	Monthly Allowance
GDP 2013 Local Currency	-	93,415,886,300	-
1% of GDP	-	934,158,863	-
per household with children	4,460,623	209	17.5
per child (0-17)	12,251,000	76	6.4

Sources: Authors calculations from World Bank (2018) (World Development Indicators), Ghana (2012) (2010 Census) and GHAMOD output file GH_2013.

Using this fixed budget, the simulations follow the approach in Evans et al. by considering different approaches to implementing a universal child transfer. The first simulation uses an approach of awarding transfers to every household that contains children and is shown in Table 8.

Table 8: Simulation 1: Results for household level child allowance

	Poverty Rates		Change	
	Pre-transfer	Post Transfer	percentage point	proportional decline
All	26.3%	25.1%	*1.1%*	*4.2%*
standard error	*0.0073*	0.0072		
95% c.i.	*24.8 27.7*	23.7 26.6		
Children (0-17)	27.5%	26.2%	*1.2%*	*4.5%*
standard error	*0.0082*	*0.0082*		
95% c.i.	*25.9 29.1*	*24.6 27.9*		
Adults (>=18)	25.2%	24.2%	*1.0%*	*4.0%*
standard error	*0.0072*	*0.0071*		
95% c.i.	*23.8 26.6*	22.8 25.6		

Source: Author's calculations using GHAMOD output data GH_2013.

A household level allowance of 17.5 Cedi each month to all households with children will reduce overall poverty from 26.3 per cent to 25.1 per cent. For children, the poverty decline simulated by this approach is slightly larger than for the whole population: reducing child poverty from 27.5 per cent to 26.2 per cent, a proportional decline of 4.5 per cent. The sensitivity and robustness tests for this simulation are shown in Annex 1 and show that this poverty difference is statistically robust and could affect 152,000 children but relies on very small differences in per-capita income for those leaving poverty that are not statistically significantly different.

Keeping the budget assumption constant in all subsequent simulations, what difference in poverty reduction would arise from transfers that are allocated for every child, rather than for households with children? The transfer using this approach is 6.4 Cedi per month, and households with larger than average families gain relative to households with fewer children, compared to the first simulation. Table 9 shows the results and confirms that per-capita child transfers give higher levels of poverty reduction, a result that was not necessarily expected given the demographic profiling shown earlier in Figures 1, 2, and 3. Overall poverty would reduce to 25 per cent, while child poverty would fall to 25.8 per cent, a six per cent proportional decline. The robustness and sensitivity tests reported in Annex 1 confirm that this poverty decline is robust, and would lift around 202,000 children out of poverty, but that underlying per-capita income changes driving this are not statistically different.

This result accords with the findings for each of the 14 middle-income countries in Evans et al. (2018): that giving transfers at the individual child level has higher poverty reduction effects compared to household level allowances.

Table 9: Simulation 2: results for child level allowance

	Poverty Rates		Change	
	Pre-transfer	Post Transfer	percentage point	proportional decline
All	26.3%	25.0%	*1.3%*	*4.9%*
standard error	0.0073	0.0072		
95% c.i.	24.8 27.7	23.5 26.4		
Children (0-17)	27.5%	25.8%	*1.7%*	*6.0%*
standard error	0.0082	0.0082		
95% c.i.	25.9 29.1	24.2 27.4		
Adults (>=18)	25.2%	24.2%	*1.0%*	*3.9%*
standard error	0.0072	0.0071		
95% c.i.	23.8 26.6	22.8 25.6		

Source: Author's calculations using GHAMOD output data GH_2013.

What would be the impact of designing transfers at the individual level but weighting the transfers to be higher for younger children? The original poverty profiles suggest that age of children is not reflected in large differences in poverty. Table 3 showed that infants (aged 0-3) do not have higher poverty rates compared to all ages of children but that the 4-6 age-group did have higher poverty rates. To follow the approach in Evans et al., we maintain the assumption of weighting to younger children when exploring weighting universal allowances by age, but Table 8 shows the results of such an approach for the combined 0-6 age group. The higher allowances were calculated at the aggregate level of the budget, and the 17.8 per cent of children in this age-group were awarded 10.59 Cedi per month, while older children get 5.44 Cedi per month (this crude 'doubling' allowances reflects a weight in the budget of 1.66 for the younger age-group).

Table 10 shows the results of repeating the individual level allocation approach shown in Table 9 but weighting higher allowances to younger children aged 6 and less. We see that poverty rates fall by a lower level than shown in Table 9. Giving young children higher levels of universal allowances does not improve poverty reduction – a result that reflects that fact that these younger children often live with other, older children. Overall poverty rates fall to 25.8 per cent and child poverty rates fall to 26.9 per cent. These results confirm the findings in Evans et al. that weighting allowances by age, does not consistently result in higher poverty reduction, but relies on national level consideration of family composition and size and other earning factors. The sensitivity and robustness of these results are reported in Annex 1 and conform to the earlier findings from the first and second simulations: robust poverty decline but no statistically significant differences in pre and post transfer incomes at the margins of poverty decline.

Table 10: Simulation 3: Results for child level allowance weighted to-0–6 year-olds

	Poverty Rates		Change	
	Pre-transfer	Post Transfer	percentage point	proportional decline
All	26.3%	25.8%	*0.4%*	*1.7%*
standard error	*0.0073*	*0.0073*		
95% c.i.	*24.8 27.7*	*24.4 27.2*		
Children (0-17)	27.5%	26.9%	*0.6%*	*2.0%*
standard error	*0.0082*	*0.0082*		
95% c.i.	*25.9 29.1*	*25.3 28.5*		
Adults (>=18)	25.2%	24.8%	*0.4%*	*1.4%*
standard error	*0.0072*	*0.0072*		
95% c.i.	*23.8 26.6*	*23.4 26.3*		

Source: Author's calculations using GHAMOD output data GH_2013.

The final simulation considers if weighting individual level universal child allowances to the bottom of the income distribution can result in higher poverty reduction compared to age-weighted or un-weighted allowances. The fixed budget was weighted to allocate higher proportions of allowance to the 40 per cent of children who live in the bottom 40 per cent of household per-capita incomes. This resulted in allowances of 9.53 Cedi per month for those in the 'bottom 40' and 4.27 Cedi per month for others.

Table 11: Simulation 4: Results for child level allowance weighted to 'Bottom 40 per cent' of households

	Poverty Rates		**Change**	
	Pre-transfer	**Post Transfer**	**percentage point**	**proportional decline**
All	26.3%	**24.4%**	*1.8%*	*6.9%*
standard error	*0.0073*	*0.0072*		
95% c.i.	*24.8 27.7*	*23.0 25.9*		
Children (0-17)	27.5%	**25.1%**	2.3%	8.5%
standard error	*0.0082*	*0.0081*		
95% c.i.	*25.9 29.1*	*23.5 26.7*		
Adults (>=18)	25.2%	**23.8%**	*1.4%*	*5.4%*
standard error	*0.0072*	*0.0071*		
95% c.i.	*23.8 26.6*	*22.4 25.2*		

Source: Author's calculations using GHAMOD output data GH_2013.

Table 11 shows the results from this simulation and shows that this approach to weighting allowances gives the highest poverty reduction (as the simple arithmetic of giving more money to those who are poor or at the margins poverty would suggest). Overall poverty falls to 24.4 per cent, a 6.9 per cent proportional decline, and child poverty falls to 25.1 per cent, an 8.5 per cent proportional decline. The robustness and sensitivity tests in Annex 1 shows that this results from 287,000 children exiting child poverty and that the difference in poverty pre and post transfers is robust. However, even for this 'best' result, the underlying differences in income at that margins of poverty are not significant.

4 Discussion

The aim of this paper is to replicate in Ghana a set of simulations of universal child allowances that had been made in an earlier paper on 14 middle income countries (Evans et al. 2018). The approach differed in some preparatory steps and focusing on a single country allowed a more detailed examination of the demographic context and where children were in the income distribution. The finding that children were not disproportionately in the lowest quintile of Ghanaian income distribution contrasted with the findings in that earlier study for the other 14 countries. However, even while children were not disproportionately in the bottom quintile, they still have higher poverty rates in Ghana – using both 'per-capita' income and when the original income definition and poverty line found in GHAMOD were used.

Focussing on a single country in this paper, rather than producing results across a large number of countries, allowed a more analytical focus on factors that influence outcomes from universal child transfers that result from demographic factors and from the nature of the income distribution. We found that children were spread widely across Ghanaian households: 67 per cent of all households contain the 46 per cent of the population aged 0-17 years. These households with children contain 87 per cent of the population, which makes the impact of any universal allowance spread over almost 9/10^{ths} of all Ghanaians – a great potential result for 'universal inclusion' but a heavy constraint on the potential to change incomes substantially if allowances were to be funded on a fixed budget. Our analysis of the income distribution showed large proportions of the population were close to the poverty line and compression of income values around that line. The household incomes of those with and without children were not greatly different at the margins of the poverty line. These findings made it important to consider how effects from transfers with small monetary values would reduce poverty and tests for the sensitivity and robustness of simulation results were developed to allow a more transparent and rigorous assessment of results than was given in the original paper (Evans et al. 2018).

The four simulations in this paper followed the approach in that paper to test if Ghana had the same results to the 14 countries used in the original study. The answer was positive- universal child allowances, funded by 1 per cent of contemporary GDP, has significant poverty reduction impacts. These poverty reduction results were higher for individual level rather than household level allocations, and individual allowances had larger impacts on poverty if they were weighted to reflect low income rather than age of children. The importance of these findings is that they show consistent results even though the demographic spread of children across the household population is so large and even though children were not disproportionately represented in the poorest quintile.

However, while the results from this paper are clear in terms of the analytical literature: replicating the earlier study and giving greater analytical understanding to the drivers of poverty reduction using universal transfers, the results for Ghanaian policy, or for future analysis using GHAMOD, are less clear. The approach of this paper provides strong encouragement to providing a clearer narrative on robustness and sensitivity when using micro-simulation and encourage the use of the output data from GHAMOD to do so. Similarly, the profiles of the population and income distribution that drive results from simulation are suggestive to encourage illustrating and contextualizing simulations rather than relying solely on model specification and testing within the model's 'front end'.

But when it comes to considering practical and applied policy change, the approaches in this paper would have to be repeated using the actual poverty and income measures that influence Ghanaian social policy: household consumption and the national poverty line that reflects household consumption. We replicated poverty using income against the Ghanaian national poverty line to ensure that the simulations and analysis conformed to a set of GHAMOD parameters, but with 10 percentage point higher poverty levels and large numbers of negative income values, the inherent applied usefulness of taking forward that approach is uncertain.

Taking forward the approach of this paper for Ghanaian policy simulation should be part of a wider discussion on how to simulate the effect of changing incomes using transfers on household consumption. This is not a simple translation as the elasticities are not simple and may not be consistent across the distribution: poorer populations tend to have more debt and have different preferences for changing food expenditure versus other expenditures, for example. That would involve having clearer approaches to reporting 'uncertainty' in simulations and of assessing the effects of assumptions that can be opaque within the model. Hopefully, the approach in this paper contributes to thinking about that.

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Annex 1

Sensitivity and robustness tests for simulations

Simulation 1: Household level allowances (Table 8)

Difference in Poverty Headcounts	Mean difference	standard error of difference	z test of poverty headcount difference	
			z	mean(diff) > 0
Difference in All Poverty	-0.012	0.0003	-41.07	Pr(Z > z) = 1.0000
Difference in Child Poverty	-0.014	0.0006	*-21.99*	*Pr(Z > z) = 1.0000*

Income Difference for 'Poverty Leavers'	sample size	weighted population (000s)	Mean Income pre-transfer		Mean Income post transfer		t-test of difference in Incomes	
			per cap Cedi	normalised to PL	per cap Cedi	normalised to PL	t	p
All	894	296	48.5	0.96	52.4	1.04		
standard errors			*0.1496*		*0.1178*		59.495	mean(diff) < 0
95% c.i.s			*48.2*	*48.7*	*52.1*	*52.3*		**Pr(T < t) = 1.0000**
Children	477	152	48.5	0.96	52.1	1.03		
standard errors			*0.0646*		*0.0709*		41.473	mean(diff) < 0
95% c.i.s			*48.3*	*48.6*	*51.9*	*52.3*		**Pr(T < t) = 1.0000**

Simulation 2: Child level allowances (Table 9)

Difference in Poverty Headcounts				
	Mean difference	standard error of difference	z test of poverty headcount difference	
			z	mean(diff) > 0
Difference in All Poverty	-0.0148	0.0004	-32.99	Pr(Z > z) = 1.0000
Difference in Child Poverty	-0.0187	0.0007	*-25.44*	*Pr(Z > z) = 1.0000*

Income Difference for 'Poverty Leavers'								
	sample size	weighted population (000s)	Mean Income pre-transfer		Mean Income post transfer		t-test of difference in Incomes	
			per cap Cedi	normalised to PL	per cap Cedi	normalised to PL	t	p
All	1,072	345	48.4	0.96	52.1	1.03		
standard errors			*0.1208*		*0.1117*		139.053	mean(diff) < 0 Pr(T < t) = 1.0000
95% c.i.s			*48.3*	*48.5*	*52.1*	*52.2*		
Children	635	202	48.3	0.96	52.3	1.04		
standard errors			*0.0468*		*0.04468*		122.745	mean(diff) < 0 Pr(T < t) = 1.0000
95% c.i.s			*48.2*	*48.4*	*52.2*	*52.4*		

Simulation 3: Weighted child allowances for 0–6-year olds (Table 10)

Difference in Poverty Headcounts				
	Mean difference	standard error of difference	z test of poverty headcount difference	
			z	mean(diff) > 0
Difference in All Poverty	-0.0049	0.0003	-18.83	Pr(Z > z) = 1.0000
Difference in Child Poverty	-0.02680	0.0004	*-14.33*	*Pr(Z > z) = 1.0000*

Income Difference for 'Poverty Leavers'								
	sample size	weighted population (000s)	Mean Income pre-transfer		Mean Income post transfer		t-test of difference in Incomes	
			per cap Cedi	normalised to PL	per cap Cedi	normalised to PL	t	p
All	353	118	49.0	0.97	51.5	1.02		
standard errors			*0.0432*		*0.0498*		52.243	mean(diff) < 0 **Pr(T < t) = 1.0000**
95% c.i.s			*49.0*	*49.1*	*51.4*	*51.59246*		
Children	204	67	49.0	0.97	51.5	1.02		
standard errors			*0.0573*		*0.0668*		39.516	mean(diff) < 0 **Pr(T < t) = 1.0000**
95% c.i.s			*48.9*	*49.1*	*51.4*	*51.6*		

Simulation 4: Weighted child allowances for bottom 40 (Table 11)

Difference in Poverty Headcounts	Mean difference	standard error of difference	z test of poverty headcount difference	
			z	mean(diff) > 0
Difference in All Poverty	-0.02106	0.0005	-39.456	Pr(Z > z) = 1.0000
Difference in Child Poverty	-0.02680	0.0009	*-30.578*	*Pr(Z > z) = 1.0000*

Income Difference for 'Poverty Leavers'	sample size	weighted population (000s)	Mean Income pre-transfer		Mean Income post transfer		t-test of difference in Incomes	
			per cap Cedi	normalised to PL	per cap Cedi	normalised to PL	t	p
All	1,524	485	47.6	0.94	53.3	1.06		
standard errors			*0.0438*		*0.0428*		171.155	mean(diff) < 0
95% c.i.s			*47.5*	*47.7*	*53.2*	*53.3*		**Pr(T < t) = 1.0000**
Children	910	287	47.4	0.94	53.3	1.06		
standard errors			*0.0580*		*0.0567*		149.721	mean(diff) < 0
95% c.i.s			*47.3*	*47.5*	*53.3*	*53.5*		**Pr(T < t) = 1.0000**