Contextual Effects of Education on Poverty in Malawi

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Abstract

The paper uses Malawian data from the Third Integrated Household Survey to investigate the presence and pattern of contextual effects of community level education on household poverty. These contextual effects reflect the presence of education externalities at the community level. I use an adaptation of the Hausman-Taylor estimator for hierchical models which controls for level-2 endogeneity of community schooling. The results show that regardless of gender, there is a significant positive effect of community level education on household welfare in rural and urban areas which is over and above that arising from education within the household. These externalities of community level education are larger for females than males. The paper finds that the return to within household education is smaller in magnitude than the community level externality of education. These findings are robust to alternative definitions of schooling and level of aggregation. The paper also finds that in both rural and urban areas, least educated households enjoy significantly larger benefits from increases in female and male years of schooling at the community level than the most educated households. This means that community level schooling not only spillovers to the rest of the community membership in terms of improved living standards, but also the positive education spillovers on household welfare are equality-inducing.

Keywords: Contextual effects; externalities; Malawi

1 Introduction

Groups of households such as communities or villages become differentiated, and that households in a group are usually interdependent which entails that what influences one group member may also influence other group members, either through direct interactions with other group members or by creating a group environment that influences individual members (Hox, 2010; Goldstein, 2011; Rabe-Hesketh and Skrondal, 2012; Dunn et al. 2014). Households in the same group may for instance be exposed to the same local policies and programmes or they may be subject to the same traditional norms regarding the roles of men and women (McCulloch et al., 2008; Goldstein, 2011). A household's

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poverty level may therefore be a result of an interplay of factors within the household and contextual factors i.e. factors outside the household.

Outside of poverty research, the idea that groups may have collective properties which influence their members independently of individual factors has attracted alot of research interest with a number of studies examining the role of contextual factors on health outcomes (e.g. Cohen et al. 2006; Mair et al. 2008; Dunn et al. 2014), student performance (e.g. Marsh et al., 2009; Morin et al., 2014), crime (e.g. Oberwittler, 2004; Winslow and Shaw, 2006), and agriculture productivity (e.g. Weir and Knight, 2007; Asadullah and Rahman, 2009; Mussa, 2015). There is however a dearth of poverty studies that have examined the role of contextual effects of education on household living standards.

These contextual effects may reflect the presence of externalities, for instance, the extent of schooling at the community level can have a positive externality effect on poverty thus leading to better economic outcomes. Such educational externalities might arise for instance as uneducated farmers learn from the superior production choices of other educated farmers in the community (Weir and Knight, 2007). The education externality could also arise when educated farmers are early innovators and are copied by those with less schooling (Knight et al., 2003). External benefits of education may also arise in a community through one person taking decisions on behalf of another person (Dreze and Saran, 1995).

The literature on the determinants of poverty (e.g. Mukherjee and Benson, 2003; Datt and Jollife, 2005; Zhang and Wan, 2006; Cruces and Wodon, 2007; Gunther and Harttgen, 2009; Echevin, 2012) has primarily tended to focus on how household level education affects poverty. A common finding in these studies is that the level of education within households lowers the likelihood of household poverty and vulnerability to poverty. What is ignored here is that two households with identical characteristics but living in communities/contexts with different average schooling may have different welfare profiles.

The nature of these contextual effects of education may be useful to quantify. The existence of education externalities has significant implications on how to evaluate the costs and benefits of investments in education as a failure to account for education externalities may lead to its under-provision. This paper looks at the relationship between poverty and education within and between households in Malawi. The objectives of this paper are twofold. First, I investigate the existence of community level education externalities on poverty in Malawi. In this regard, three questions are explored: Are there community level externalities of education? Do the externalities vary with gender? Are the externalities larger or smaller in size than the internal returns to education?

The second objective of this paper relates to an understanding of who benefits more from education externalities. Do households with little or no education benefit more from living in communities where some inhabitants are educated? Uneducated households that reside in communities where some members are educated-the so-called proximate illiterates (Basu and Foster, 1998)- are a priori expected to be better off in terms of welfare than their counterparts who stay in communities where nobody is educated-the so-called isolated illiterates (Basu and Foster, 1998).

The rest of the paper is structured as follows. Section 2 looks at trends in poverty, inequality, and economic growth in Malawi. Section 3 presents the methodology and a description of the data and variables used. This is followed by the empirical results in Section 4. Finally, Section 5 concludes.

2 Growth, Poverty, and Education in Malawi

The Malawian government has pursued poverty reduction efforts through various strategies emphasizing economic growth, infrastructure development, and the provision of basic social services. These strategies include the Poverty Alleviation Program (1994); the Malawi Poverty Reduction Strategy (2002-2005); and, more recently, the Malawi Growth and Development Strategy (MGDS) (2006-2011 and 2011-2016). Although Malawi has experienced a strong economic growth performance in the recent past, the impact of this growth on poverty has been mixed.

Table 1 provides selected economic indicators for Malawi over the period 2004 and 2014. The economy grew at an average annual rate of 6.2% between 2004 and 2007, and marginally decelerated to an average growth of 6.1% between 2008 and 2014. Over the same period, the agriculture sector was by far Malawi's most important contributor to economic growth, with a contribution averaging 34.0% to overall GDP growth . Given that economic growth was primarily driven by growth in the agriculture sector, and considering that about 90% of Malawians live in farm households (Benin et al. 2012), one would expect that this impressive growth would lead to significant reductions in poverty.

Official poverty statistics however indicate that the high economic growth rates could only translate into marginal poverty reduction. The poverty figures in Table 1 show that the percentage of poor people in Malawi was 52.4% in 2004, and slightly declined to 50.7% in 2011 . Interestingly, the high economic growth rate had contrasting effects on rural and urban poverty. For the period 2004-2011, the poverty headcount in rural areas minimally increased from 55.9% to 56.6% while urban poverty declined from 25.4% to 17.3%. Ironically, this dismal poverty reduction performance coincided with the Farm Input Subsidy Program (FISP), which every year provides low-cost fertilizer and improved maize seeds to poor smallholders who are mostly rural based (Chirwa and Dorward, 2013). Implementation of the FISP started in the 2005/6 cropping season, and in the 2012/13 financial year, the programme represented 4.6% of GDP or 11.5% of the total national budget (World Bank, 2013).

The formal education system in Malawi comprises of three levels namely; primary, secondary, and post secondary. Education at all three levels is not compulsory. The

Malawi government cognizant of the crucial role that human capital accumulation and development plays in fostering economic growth among other benefits introduced free primary education (FPE) in 1994. With FPE parents no longer have to pay fees for the primary education of children who attend government schools. Private primary schools however continue to charge fees. Increasing access to primary and secondary education is one of the main priority areas identified in the MGDS.

Table 2 presents levels and trends in: a) adult literacy rates, b) primary enrolment rates, c) primary school dropout rates, and d) average years of schooling between 2004 and 2011. The proportion of the population aged 15 years and over that is able to read and write increased marginally from 64% in 2004 to 65% in 2011; suggesting limited progress in improving adult literacy in Malawi. The proportion of adults who are literate is higher in urban areas than in rural areas. Furthermore, the literacy rate for rural areas has remained almost unchanged while it has increased by about 3 percentage points between 2004 and 2011.

For both years, progress has been made in increasing primary net enrolment rates. However, primary enrolment levels in rural areas are lower than those for urban areas. The internal efficiency of primary school system as measured by the dropout rate seems to have improved over the five year period. Average schooling also registered some improvements; from 4.1 years to 5.0 years in 2004 and 2011 respectively. These improvements in years of schooling are more pronounced in rural areas where it increased by 20.4% as compared to 5.5% for urban areas. Although the levels are still low, these statistics suggest that Malawi has registered some progress with respect to primary enrolment, years of schooling, and internal efficiency.

3 Empirical Strategy

3.1 Modeling Contextual Effects of Education

Data for analysing poverty is almost always hierarchically structured in the sense that households are nested in communities, and the communities in turn are nested in districts. Hierarchical linear models (HLMs) or linear multilevel models are useful for analyzing this type of data (McCulloch et al., 2008; Hox, 2010; Rabe-Hesketh and Skrondal, 2012; Cameron and Miller, 2015). Households in the same cluster/community are likely to be dependent because they are exposed to a wide range of common observed and unobserved community factors such as the same traditional norms regarding the roles of men and women. This dependency means that standard errors from a standard linear regression model are downward biased, and inferences about the effects of the covariates may lead to many spurious significant results (Hox, 2010; Cameron and Miller, 2015). Beyond this, a key attraction of HLMs is that they are useful for modeling contextual effects (Arpino and Varriale, 2010; Castellano et al. 2014).

Consider the following two level linear random-intercept model for household i ($i = 1....n_j$) in community j ($j = 1....J_l$)

$$\begin{aligned} Level\ 1 &: \ln y_{ij} = \beta_{0j} + \beta_1' x_{ij} + \pi' q_{ij} + \varepsilon_{ij} & (1) \\ Level\ 2 &: \beta_{0j} = \beta_0 + \delta' z_j + u_j & (2) \end{aligned}$$

where; in the level 1 model, $\ln y_{ij}$ is the log of per capita annualized household consumption expenditure, β_{0j} is a community-specific intercept, x_{ij} is a vector of observed household level (level 1) education variables, β_1 is its associated coefficient vector, q_{ij} is a vector of other observed household level (level 1) characteristics, z_j a vector of community level variables which capture availability in a community of social and economic services such as paved roads, clinics, banks, π and δ are coefficient vectors of the level-1 and level-2 controls, and $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$ is a household-specific idiosycratic error term. In the level 2 model, β_0 is the overall intercept, and $u_j \sim N(0, \sigma_u^2)$ are community-level spatial effects (random intercepts). u_j and ε_{ij} are assumed to be independent. I measure education by using average years of schooling in a household, and this is gender-disaggregated to measure the possibility that education can have a gender-differentiated effect on poverty. As a sensitivity check, maximum years of schooling is also used. The assumptions about u_j and ε_{ij} imply that $\zeta_{ij} \sim N\left(0, \sigma_\zeta^2\right)$ where $\zeta_{ij} = u_j + \varepsilon_{ij}$ and $\sigma_\zeta^2 = \sigma_u^2 + \sigma_\varepsilon^2$.

The two levels can compactly be re-specified by substituting equation (2) into (1) to get

$$\ln y_{ij} = \beta_0 + \beta_1' x_{ij} + \pi' q_{ij} + \delta' z_j + u_j + \varepsilon_{ij} \tag{3}$$

Equation (3) implicitly assumes that the effect on poverty of education is the same between communities and within communities. As shown by both Neuhaus and Kalbfleisch (1998) and Arpino and Varriale (2010), micro (household) and macro (community) level effects of a variable can be different, and ignoring these differences can give misleading results. Community level mean education can effect household poverty even after controlling for the households's own education level i.e. there are possible community level contextual effects of education.

To accommodate these contextual effects, I decompose x_{ij} into between $\bar{x}_j = \frac{1}{n_j}\sum_{i=1}^{n_j} x_{ij}$ and within $(x_{ij} - \bar{x}_j)$ community components such that $x_{ij} = \bar{x}_j + (x_{ij} - \bar{x}_j)$. I then extend equation (3) by allowing different effects of the two components on poverty, i.e. replacing $\beta_1' x_{ij}$ in (3) by $\beta_w' (x_{ij} - \bar{x}_j) + \beta_b' \bar{x}_j$. to get the following model which simultaneously accommodates both between and within-community effects

$$\begin{aligned} \ln y_{ij} &= \beta_0 + \beta_w' (x_{ij} - \bar{x}_j) + \beta_b' \bar{x}_j + \pi' q_{ij} + \delta' z_j + u_j + \varepsilon_{ij} & (4) \\ &= \beta_0 + \beta_w' x_{ij} + \theta' \bar{x}_j + \pi' q_{ij} + \delta' z_j + u_j + \varepsilon_{ij} \end{aligned}$$

where β_w represents the within-community effect, and β_b represents the between-community effect of education. The difference, $\theta = \beta_b - \beta_w$, represents the contextual effect i.e. the additional effect of education at the community level that is not accounted for at the household level. The contextual effect essentially represents community level externalities of education. A test of the hypothesis that $\theta = 0$, amounts to testing that there are no externality effects of schooling at the community level on poverty. The sign and magnitude of θ respectively indicate the direction and size of the externality effect. A positive (negative) externality effect of community level schooling on poverty holds if $\theta > 0\,(\theta < 0)$. In order to check the robustness of the results to how community level schooling is measured, I also use gender-disaggregated maximum years of schooling in a community.

When there are no education externalities, $\beta_b = \beta_w$, and equation (4) reduces to equation (3). Both z_j and $\bar{x}_j$ are community level variables, a key difference is that for z_j information is only available at the community while for $\bar{x}_j$ information is available at the household level as well. I exclude each household's value of x when generating the community level means of education $\bar{x}_j$.

3.2 Contextual Effects and Endogeneity

A possible concern with the contextual effect θ is that it can potentially be endogenous. For instance, education at the community level may be correlated with unobserved determinants of local development, and this selection on unobservables may lead to biased results. This concern is however assuaged by the fact that the model controls for unobserved community level random effects through u_j. These random effects for example capture differences in exposure to social policy programmes between communities. Moreover, the paper also controls for community level access to and availability of health and economic infrastructure through z_j.

This notwithstanding, there are other sources of endogeneity to worry about. In hierchical models there are two types of endogeneity depending on the correlation between the random error components and the covariates: level-1 endogeneity where $cov(x_{ij}, \varepsilon_{ij}) \neq 0$, $cov(\bar{x}_j, \varepsilon_{ij}) \neq 0$, $cov(q_{ij}, \varepsilon_{ij}) \neq 0$, and $cov(z_j, \varepsilon_{ij}) \neq 0$, and level-2 endogeneity which holds when $cov(x_{ij}, u_j) \neq 0$, $cov(\bar{x}_j, u_j) \neq 0$, $cov(q_{ij}, u_j) \neq 0$, and $cov(z_j, u_j) \neq 0$ (Ebbes et al., 2004; Castellano et al. 2014). Regression coefficients can be biased and inconsistent in the presence of these two types of dependencies. In keeping with previous poverty studies (e.g. Mukherjee and Benson, 2003; Datt and Jollife, 2005, Cruces and Wodon, 2007), the choice of covariates is driven by an exogeneity criteria i.e. only those covariates that are determined outside of the current economic system of the household but influence the current level of household welfare are included. Using the exogeneity criteria ensures that the covariates are level-1 exogenous, this however leaves the problem of level-2 endogeneity unresolved.

The inclusion of the community level mean education resolves the problem of level-2 endogeneity arising from omitted variables, but it creates another form of level-2 endogeneity emanating from measurement error. The use of community level sample mean values of education instead of the population community mean entails a measurement error that can lead to attenuated contextual coefficients (Grilli and Rampichini, 2006). An adaptation of the Hausman and Taylor (1981) estimator from panel data econometrics can be used to overcome this problem in hierchical models (Ebbes et al., 2004; Castellano et al. 2014).

A key attraction of the Hausman-Taylor (HT) estimator is that it addresses the problem of level-2 endogeneity without requiring any additional exogeneity assumptions or external instrumental variables (Castellano et al. 2014). The HT estimator generates instruments from the available data (internal instruments) instead (Ebbes et al., 2004). I use the adapted HT estimator to address the measurement error problem in community level mean education. Consider $X_{ij} = [x_{ij} : q_{ij}]$ and $F_j = [\bar{x}_j : z_j]$, where the variables in sets x_{ij} (household level education), q_{ij}, and z_j are level-1 and level-2 exogenous while in contrast, the variables in $\bar{x}_j$ are level-1 exogenous but level-2 endogenous. I then use $\bar{q}_j$ as internal instruments for $\bar{x}_j$, and the remaining variables serve as their own instruments

As a diagnostic check for level-2 endogeneity, I use the Hausman-type test developed by Hausman and Taylor (1981). The null of level-2 exogeneity is tested by estimating fixed-effects and random-effects versions of equation (4). Irrespective of whether or not level-2 endogeneity exists, fixed-effects estimation gives unbiased estimates of the within-coefficients in equation (4) , in contrast, random-effects estimation yields biased estimates when level-2 endogeneity is present (Ebbes et al., 2004; Castellano et al. 2014).

3.3 Data description and variables used

The data used in the paper are taken from the Third Integrated Household Survey (IHS3) conducted by Malawi's National Statistical Office (NSO). It is a multi-topic survey which is statistically designed to be representative at both national, district, urban and rural levels. It was conducted from March 2010 to March 2011. A stratified two-stage sample design was used. At the first stage, enumeration areas, representing communities, as defined in the 2008 Population Census, stratified by urban/rural status were selected with probability proportional size. The second stage used systematic random sampling to select households.

The survey collected information from a sample of 12271 households; 2233 (representing 18.2%) are urban households, and 10038 (representing 81.8%) are rural households. A total of 768 communities were selected from 31 districts across the country[1]. In each

[1] Malawi has a total of 28 districts. However, the IHS3 treats Lilongwe City, Blantyre City, Mzuzu City, and Zomba City as separate districts. Likoma district is excluded since it only represents about 0.1% of the population of Malawi, and it was determined that the corresponding cost of enumeration

district, a minimum of 24 communities were interviewed while in each community a total of 16 households were interviewed. In addition to collecting household level data, the survey collected employment, education, and other socio-economic data on individuals within the households. It also collected community level information on access to basic services.

In order to capture possible locational differences, the paper distinguishes between rural and urban households, and I use the new annualized consumption aggregate for each household generated by Pauw et al. (2016) instead of the official aggregate as a welfare indicator i.e. the dependent variable. This choice is necessitated by the fact that the food component in the official aggregate is based on conversion factors which have been shown to have inconsistencies and errors (Verduzco-Gallo and Ecker, 2014). The computation of quantities of food consumed is based on conversion factors which are used to covert non-standard units of measurements such as pails, basins, and pieces into standard units such as kilograms and grams. The new aggregate uses a new set of conversion factors developed by Verduzco-Gallo and Ecker (2014) to generate the new food component. The official and the new consumption aggregates however have the same non-food component.

In addition to the education variables already discussed, the paper controls for three groups of independent variables namely; household, community, and fixed effects variables. The choice of variables is guided by previous literature (e.g. Mukherjee and Benson, 2003; Datt and Jollife, 2005, Cruces and Wodon, 2007) on determinants of poverty. At the household level, I include a set of demographic variables: number of individuals aged below 9 years, number of individuals aged 10-17 years, number of females aged 18-59 years, number of males aged 18-59 years, the number of the elderly (above age 60) household members, the square of household size, linear and quadratic terms in the age of the household head to capture possible life cycle effects, and a dummy variable for male head of household.

I also control for employment represented by the number of household members employed in the primary, secondary, and tertiary industries. In terms of agricultural variables, I include the number of crops the household cultivated that are not maize or tobacco, a measure of the diversity of crop cultivation. These include the food crops cassava, groundnut, rice, millet, sorghum, and beans, and the cash crops cotton. Another agriculture variable included is the area of cultivated land that is owned by the household. The agriculture variables are included in the rural regressions only.

At the community level, I include community level health infrastructure and economic infrastructure indices to measure availability of and access to basic medical and economic infrastructure and services in a community. The two indices are constructed by using multiple correspondence analysis (MCA) (see e.g. Asselin (2002) and Blasius and Greenacre (2006) for more details). The health infrastructure index is constructed

would be relatively high. The total number of districts or strata covered is therefore 31.

from information on the availability in a community of the following: a place to purchase common medicines, a health clinic, a nurse, midwife or medical assistant, and groups or programs providing insecticide-treated mosquito bed nets free or at low cost. The economic infrastructure index is based on the presence of the following in a community: a perennial and passable main road, a daily market, a weekly market, a post office, a commercial bank, and a microfinance institution.

Two sets of spatial and temporal fixed effects variables are included. I include agro-ecological zone dummies which capture zone level fixed effects. There are eight agro-ecological zones. The agro-ecological zone dummies control for differences in land productivity, climate, and market access conditions in an area. Agro-ecological zones are rural, consequently, they only appear in the rural regression. Being an agro-based economy, household welfare in Malawi may vary across the year due to possible seasonal effects. I account for these variations by including three seasonal dummies reflecting the harvest, postharvest, and preplanting periods. I use a Wald test to check for the presence of these fixed effects. Detailed definitions and summary statistics for all the independent variables are given in Table 3.

4 Results

4.1 Regression Results

Hausman-Taylor tests for the null of level-2 exogeneity of community level average schooling return $\chi 2 = 99.5$ and $\chi 2 = 124.0$ for the rural and urban models respectively. This means that in both rural and urban areas, community level average schooling suffers from level-2 endogeneity arising from measurement error. The determinants of poverty results for rural and urban areas are reported in Table 4. For comparison purposes, three sets of results for each area are reported; one does not account for education contextual effects and the other two allow for contextual effects of education. For the two models with contextual effects, one is based on the standard hierchical linear model (HLM) and the other addresses level-2 endogeneity by using the Hausman-Taylor (HT) adaptation.

In all the models, the Wald test results point to the presence of significant seasonal and agroecological effects. Consequently, seasonal and agroecological dummies are included. The Wald test results further indicate that all the variables included in the models are jointly statistically significant. A general pattern in the three sets of results for each area can be noted: the signs and statistical significance of all the covariates are generally similar regardless of whether or not contextual effects are accounted for or whether or not the problem of level-2 endogeneity is addressed. I now turn to a discussion of the results for the noncontextual variables before moving on to a more detailed look at the contextual effect of education on welfare. The interpretation and discussion is based on the HT results for each area.

There is a similar pattern regarding the sizes of the coefficients and individual statistical significance of the variables that are not entered as contextual variables. Gender of the household head emerges as a significant correlate of poverty. Holding other things constant, female headed households are poorer than male headed households in rural areas. Precisely, using the HT model, the results show that their per capita consumption is 17.0% lower than that of male headed households. A comparison with a previous study by Mukherjee and Benson (2003) reveals some differences in the relationship between gender and poverty in Malawi. Unlike the finding in this paper, they found a rather puzzling result that in rural areas of Malawi, male headed households are poorer. A negative sign on the gender dummy in urban areas suggests that this gender difference is in favour of female headed households. This rather counterintuitive finding in urban areas is however consistent with what Mukherjee and Benson (2003) also found.

The age of the household head has a significant inverted u-shaped relationship with standard of living in both areas. Precisely, using results which account for contextual factors, I find that household living standards increase with the age of the head up to 65 years (90th percentile) in rural areas, and 74 years (99th percentile) in urban areas, and diminish thereafter. This means that there are significant life cycle effects which reflect increased earning capacity arising from greater experience and smoothing of consumption over one's lifetime. This common finding (e.g. Grootaert,1997; Datt and Jollife, 2005) is however in stark contrast to a previous study by Mukherjee and Benson (2003) who found a negative relationship between age and welfare in Malawi.

In terms of household composition, the results indicate that in the rural model, the coefficients are more negative for children aged 0-9 and the elderly (aged 60 above) than for the economically active category (i.e. 18-59 age category). This means that an increase in dependent household members leads to a larger welfare reduction than an increase in those in the economically active group. For the urban model, only the coefficient for children aged 0-9 is more negative than for the economically active group while that for the elderly is less negative Moreover, in both areas, an increase in the household of female adults in the economically active group does not affect per capita consumption. In contrast, the effect on welfare following the addition in a household of a male adult in the economically active group is statistically significant in both areas, but, it is larger in rural areas (30.9%) than in urban areas (about 23.1%). Considering that economic opportunities tend to favour men, one would expect a reverse pattern.

The coefficient on the square of household size is positive and statistically significant, and this together with the finding that the household composition variables are negatively and significantly related to welfare suggests that there is a U-shaped relationship between household size and living standards. This is a common empirical finding (see e.g., Lanjouw and Ravallion, 1995; Lipton and Ravallion, 1995; Mukherjee and Benson, 2003; Datt and

Jollife, 2005). The use of per capita consumption implicitly assumes away the importance of economies of scale of household size in consumption i.e. it costs less to house two people than to house two individuals separately. and the role of household composition i.e. food needs depend on age and gender. Some studies have shown that the impact of household size on poverty disappears once these two problems are addressed (e.g. Lanjouw and Ravallion, 1995; White and Masset, 2003).

To make certain that the effect of household size on consumption in Malawi is not driven by the per capita normalization, I re-estimated the poverty models by adjusting consumption for composition and economies of scale[2]. In both rural and urban models, the results show that the coefficients on the different age-sex composition variables are negative and significant, but critically, the coefficients are smaller in size compared to those from the per capita normalisation. For instance, in the rural model, the coefficient on children below 9 is -0.038 when the economies of scale parameter is 0.4, and then the coefficient rises to -0.239 for an economies of scale parameter of 1. Similarly, for urban areas, the coefficient on children below 9 is -0.029 when the economies of scale parameter is put at 0.4, it then rises to -0.226 when the parameter is 1. This means that the negative relationship between household size and welfare is not necessarily driven by the per capita normalisation but that larger households are indeed poorer than smaller ones. Besides, using the per capita measure merely leads to an overestimation of the impact of household size on poverty.

Employment as measured by the number of adults in a household employed in the primary, secondary, and tertiary economic sectors exhibit a mixed pattern. There are no statistically significant welfare advantages to finding employment in the primary (agriculture, fishing, mining, etc.) and secondary (manufacturing) sectors. However, regardless of location, employment in the tertiary sector (sales and service industries) has a statistically significant, and positive effect on welfare. Holding all else constant, having an additional household member employed in a tertiary industry occupation increases consumption by 19.9% in rural areas and by 12.6% in urban areas. Notably, Mukherjee and Benson (2003) found a rather counterintuitive result that employment in a tertiary occupation does not influence welfare in urban areas in Malawi.

In terms of agriculture, the results indicate that land ownership and crop diversification have statistically significant effects on poverty. Holding other factors constant, an increase in cultivated area per capita by an acre increases per capita consumption in rural Malawi by 8.0%. Crop diversification beyond maize and tobacco leads to a rather modest *ceteris paribus* increase in living standards of 3.9%. Both health and economic infrastructure in the community have a positive effect on household welfare. Furthermore,

[2] Instead of normalising by household size, I normalise consumption by $\mathbf{A} = (E)^{\theta}$, where E a nutrition-based age and sex-specific adult equivalents by the WHO (1985), and $1 - \theta$ is a measure of economies of scale. I experimented with the following values of economies of scale 0.4, 0.6, 0.8, and 1.0.

in rural areas, improvements in economic infrastructure such as a perennial and passable main road, a daily market, a weekly market have a larger effect on welfare than health infrastructure such as clinics and nurses. However, a reverse pattern is observed in urban areas.

I now turn to a key focus of this paper, and discuss results on the existence, nature and form of contextual effects emanating from community level education. In discussing these results, I look at both the within and contextual effects of education. As noted already, the within effects represent internal returns to education while the contextual effects capture externalities of community level education i.e. external returns to education. The Wald test results in Table 4 confirm that jointly there are significant contextual effects of education.

As would be expected in the presence of measurement error, the coefficients on within and between community schooling are attenuated as one moves from the standard HLM results to the HT results. All the within-household education variables have statistically significant positive effects on per capita consumption; implying that the level of education in a household reduces the likelihood of poverty in Malawi. Moreover, the internal returns to education are quantitatively sizable. The returns to education are however are gender-differentiated. For instance, in rural areas and holding other factors constant, an additional year of schooling for females in a household leads to a 4.2% increase in per capita consumption while for males the corresponding effect is 3.0%.

Irrespective of gender, the results further indicate that there are spatial differences in the size of the intrahousehold returns to education with urban areas exhibiting quantitatively larger returns than rural areas. For example, the marginal effect of the years of education for females in a household is 4.2% in rural areas while it jumps to 5.0% in urban areas. This rural-urban difference in the role of education perhaps reflects the paucity of remunerative economic opportunities in rural areas of Malawi (Mukherjee and Benson, 2003).

The finding that household level education reduces poverty is common in the poverty literature (see e.g. Mukherjee and Benson, 2003; Datt and Jollife, 2005, Cruces and Wodon, 2007), and is therefore not surprising. The question is, does education beyond the household have any impact on a household's welfare? Are there positive externalities of community level education? The results do show that regardless of gender there is a significant positive effect of community level education on household welfare in rural and urban areas which is over and above that arising from education within the household.

In rural areas, the marginal return of average years of schooling of female and male community members are 7.2% and 6.1% respectively. For the urban sample, the external returns to community education are 9.9% and 7.9% for females and males respectively. Just like the impact of within-household education, the size of the contextual effect of education is also gender-dependent; the contextual effect is larger in magnitude for female education than male education in both rural and urban areas. The external returns to community education are also different spatially, here the results show that the returns are more pronounced in urban areas than in rural areas for both male and female education.

A comparison of the two sets of returns to education shows that the size of this community education externality is larger than that of the intrahousehold return to education. For instance, the rural results indicate that the marginal return of female years of schooling in a household is 4.2% while the corresponding impact of schooling at the community level is 7.2%. For the urban sample, the model results indicate that holding all else constant, an increase in the average years of schooling of females in a community is associated with a 9.9% increase in per capita consumption while the partial return of within-household education is smaller at 5.0%. This is important as it suggests that education has both private and public good properties, and that there are significant welfare benefits that accrue to households that reside in a community where some members are educated. Moreover, these external benefits of education are larger than internal benefits of education.

I delve deeper into the pattern of this benefit by examining whether households with little or no education benefit more from living in communities where some inhabitants are educated. Apriori one would expect the inter-household education externality to be relatively more pronounced for those households with little or no schooling than for those with high levels of schooling. Mussa (2015) for example finds that in the context of maize production in Malawi, farmers who reside in households where members are not educated have relatively higher production, and lower production uncertainty if they live in communities where some inhabitants are educated.

I empirically answer this question by looking at how the positive education externality varies across the first (bottom 10%) decile and the last (top 10%) decile of female and male average years of schooling in a household. This is done by re-estimating the poverty regressions for each one of the two deciles. Households in the first decile of schooling are the least educated while those in the last decile are the most educated on average. The results are presented in Table 5. The results provide some useful insight into the nature, form, and pattern of education externalities on household welfare.

Across the deciles, the sizes coefficients on average years of schooling of females and males in a community are generally consistent with expectations. In both rural and urban areas, least educated households enjoy significantly larger benefits from increases in female and male years of schooling at the community level than the most educated households. The rural results for instance indicate that the marginal returns of an additional year of female and male schooling in a community are respectively 5.5% and 3.3% for the households in the bottom 10%. However, the corresponding externalities of community schooling for the top 10% are statistically not different from zero. Similar to the rural results, the urban results show that the externality of female education for the least educated households is statistically significant and larger than that for the most educated households. In contrast to the rural results, the externality for households in the top 10% in urban areas is statistically different from zero.

Notably, the sizes of these significant externalities for the bottom and top 10% are larger for females than for males. This is consistent with the overall finding earlier of gender-differentiated community externalities of education. The finding that the least educated households enjoy significantly more from spillovers of community education coupled with the fact that poorest households tend to have the lowest level of education means that the positive education spillovers on household welfare are equality-inducing. Additionally, this equalising effect of community education is stronger for female education.

It is important to put these results in some context. The results can be placed in the broader literature on returns to education. In general, the literature on returns to education in the labour market finds about an 8-10% return to an extra year of education (Psacharopoulos, 1994; Psacharopoulos & Patrinos, 2002). In this paper, I find that the internal returns to education are in the range 3-5% while external returns to education vary from 6.1% to 9.9%.

In Table 6 I show how average per capita expenditure in US$ changes following a partial one year increase in female and male education within a household and at the community level. The associated changes in per capita expenditure are quantitatively substantial.. For example, for rural areas, an extra year of female education within a household is on average worth about US$14.13 in additional expenditure. In contrast, a one-year increase in community level education of females is on average associated with an extra expenditure of US$24.22.

4.2 Robustness Checks

Is the evidence of the existence of externalities of education sensitive to the way schooling is captured? The above results are based on the average years of schooling in a household and a community. It can be argued that the externality of schooling can best be captured by the highest level of education among all household or all community members. Take the case of crop production decisions such as application of fertiliser, the one who receives the highest education in the household or at the community can help other household and community members in making these decisions. I therefore re-estimated the above models, and replaced household average years of schooling with the maximum years of schooling in a household, and average years of schooling in a community with the maximum of years of schooling in a community. The results are reported in Table 7, and they show statistically significant and sizable community level externalities of education found earlier.

Specifically, the finding that the externalities of community level education are larger than the internal return to education remains unchanged even when this new definition is adopted, and the internal and external returns of education are larger for females than for males. Furthermore, returns to education are larger in magnitude in rural areas than in urban areas. are All this implies that the finding that there are positive education spillovers of community schooling is not sensitive to how schooling is measured. The rest of the analysis is therefore based on average years of schooling at the household and community levels.

Another concern that can be put forward is that aggregating schooling at the community level may not be appropriate given the fact that the survey was not designed to be representative at the community level i.e. the survey was designed to be representative at the district level. I re-estimated the HT model with average years of schooling of males and females at the district level. The results are displayed in Table 8. Here again I find significant externalities of education on household welfare. Moreover, the pattern and nature of the education externalities is the same as that observed earlier when aggregation was at the community level. Thus, the existence of education externalities on poverty is not driven by the level of aggregation.

5 Concluding Remarks

The paper has used Malawian data from the Third Integrated Household Survey to investigate the presence and pattern of contextual effects of community level education on household poverty. These contextual effects reflect the presence of education externalities at the community level. I have used an adaptation of the Hausman-Taylor estimator for hierchical models which controls for level-2 endogeneity of community schooling. The results show that regardless of gender, there is a significant positive effect of community level education on household welfare in rural and urban areas which is over and above that arising from education within the household. These externalities of community level education are larger for females than males.

The paper has found that the return to within household education is smaller in magnitude than the community level externality of education. These findings are robust to alternative definitions of schooling and level of aggregation. The paper has also found that in both rural and urban areas, least educated households enjoy significantly larger benefits from increases in female and male years of schooling at the community level than the most educated households. This means that community level schooling not only spillovers to the rest of the community membership in terms of improved living standards, but also the positive education spillovers on household welfare are equality-inducing.

Significantly, the findings here imply that least educated households are not necessarily worse-off in terms of welfare as they may benefit from living in communities where some members are educated. These social benefits emanating from educating individual members of a society further strengthen the view that when evaluating the costs and benefits of education investments social returns should be included as a failure to do so may underestimate the benefits of education and lead to its under-provision.

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Table 1: Trends and levels of economic growth, poverty, and inequality

Indicator/Area	2005	2011
GDP growth	6.2[a]	6.1[b]
Poverty headcount		
National	52.4	50.7
Rural	55.9	56.6
Urban	25.4	17.3
Gini Coefficient		
National	0.390	0.452
Rural	0.339	0.375
Urban	0.484	0.491

[a] Average GDP growth for 2004-2007, [b] average GDP growth for 2008-2014.
Source: NSO (2005, 2012a, 2012b), RBM Annual Economic Report (various issues)

Table 2: Trends and levels using some education statistics, 2004-2011

Indicator	Malawi		Rural		Urban	
	2004	2011	2004	2011	2004	2011
Adult literacy	63.9	65.4	60.9	60.7	85.6	89.0
Net primary enrolment rate	80.0	85.8	79.3	84.6	86.8	92.7
Gross primary enrolment rate	112.9	120.0	112.0	119.2	122.4	125.1
Primary dropout rate	5.1	1.3	5.3	1.4	4.1	0.9
Average years of schooling	4.09	4.96	3.63	4.37	7.59	8.01

Source: NSO (2005, 2012a)

Table 3: Descriptive statistics of variables

Variable	Rural		Urban	
	Mean	SD	Mean	SD
sex of the household head (1 if head is male, 0 otherwise)	0.747	0.435	0.817	0.387
age of HH head	42.934	16.682	38.724	13.409
# of people in HH under 9 years	1.561	1.306	1.275	1.173
# of people in HH 10-17 years	0.948	1.114	0.862	1.080
# of females in HH 18-59 years	0.955	0.571	1.119	0.723
# of males in HH 18-59 years	1.838	1.000	2.249	1.145
# of people over 60 years	0.263	0.546	0.125	0.404
Average years schooling of females in a household	3.047	2.692	5.605	3.741
Average years schooling of males in a household	3.771	3.084	6.584	3.935
Average years schooling of females in a community	3.047	1.190	5.605	1.561
Average years schooling of males in a community	3.771	1.245	6.584	1.519
# of HH members primary industry occupation	0.041	0.226	0.033	0.186
# of HH members secondary industry occupation	0.037	0.222	0.100	0.316
# of HH members tertiary industry occupation	0.100	0.329	0.560	0.691
land per capita in acres	0.121	0.460	-	-
number of crops grown by HH other than maize/tobacco	0.189	0.576	-	-
index of economic infrastructure	-0.145	0.857	0.651	1.292
index of health infrastructure	-0.846	1.190	-0.572	1.054
zone1 (Nsanje, Chikwawa districts)	0.073	0.261	-	-
zone2 (Blantyre, Zomba, Thyolo, Mulanje, Chiradzulu, Phalombe districts)	0.226	0.418	-	-
zone3 (Mwanza, Balaka, Machinga, Mangochi districts)	0.178	0.383	-	-
zone4 (Dedza, Dowa, Ntchisi districts)	0.110	0.313	-	-
zone5 (Lilongwe, Mchinji, Kasungu districts)	0.131	0.337	-	-
zone6 (Ntcheu, Salima, Nkhotakota districts)	0.107	0.309	-	-
zone7 (Mzimba, Rumphi, Chitipa districts)	0.107	0.309	-	-
zone8 (Nkhatabay, Karonga districts)	0.068	0.252	-	-
season1 (1 if household was interviewed in March-April, 0 otherwise): Base	0.189	0.392	0.172	0.378
season2 (1 if household was interviewed May-August, 0 otherwise)	0.275	0.446	0.259	0.438
season3 (1 if household was interviewed in September-November, 0 otherwise)	0.298	0.457	0.321	0.467
season4 (1 if household was interviewed in December-February, 0 otherwise)	0.238	0.426	0.248	0.432
Observations	10038		2233	

Variable	Rural						Urban					
	No CE	SE	HLM CE	SE	HT CE	SE	No CE	SE	HLM CE	SE	HT CE	SE
HH average years of schooling of females	0.039^{***}	(0.002)	0.039^{***}	(0.002)	0.042^{***}	(0.003)	0.046^{***}	(0.004)	0.047^{***}	(0.004)	0.050^{***}	(0.007)
HH average years of schooling of males	0.027^{***}	(0.002)	0.028^{***}	(0.002)	0.030^{***}	(0.003)	0.041^{***}	(0.004)	0.043^{***}	(0.004)	0.046^{***}	(0.006)
Comm. average of schooling of females			0.045^{***}	(0.012)	0.072^{***}	(0.018)			0.066^{***}	(0.023)	0.099^{***}	(0.032)
Comm. average of schooling of males			0.037^{***}	(0.011)	0.061^{***}	(0.020)			0.071^{***}	(0.023)	0.079^{***}	(0.024)
sex of the household head	0.157^{***}	(0.014)	0.158^{***}	(0.014)	0.157^{***}	(0.015)	-0.076^{*}	(0.039)	-0.068^{*}	(0.039)	-0.050^{***}	(0.012)
age of HH head	0.013^{***}	(0.002)	0.013^{***}	(0.002)	0.012^{***}	(0.002)	0.027^{***}	(0.006)	0.026^{***}	(0.006)	0.025^{***}	(0.007)
square of age of HH head	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)	-0.000^{***}	(0.000)
# of people in HH under 9 years	-0.330^{***}	(0.009)	-0.330^{***}	(0.009)	-0.329^{***}	(0.014)	-0.329^{***}	(0.020)	-0.331^{***}	(0.020)	-0.329^{***}	(0.023)
# of people in HH 10-17 years	-0.329^{***}	(0.010)	-0.328^{***}	(0.010)	-0.327^{***}	(0.015)	-0.256^{***}	(0.022)	-0.255^{***}	(0.022)	-0.255^{***}	(0.029)
# of females in HH 18-59 years	-0.011	(0.016)	-0.011	(0.016)	-0.008	(0.017)	-0.035	(0.029)	-0.033	(0.029)	-0.027	(0.027)
# of males in HH 18-59 years	-0.311^{***}	(0.013)	-0.309^{***}	(0.013)	-0.309^{***}	(0.019)	-0.222^{***}	(0.025)	-0.221^{***}	(0.025)	-0.231^{***}	(0.032)
# of people over 60 years	-0.338^{***}	(0.018)	-0.336^{***}	(0.018)	-0.337^{***}	(0.021)	-0.143^{**}	(0.058)	-0.146^{**}	(0.058)	-0.163^{**}	(0.069)
square of household size	0.017^{***}	(0.001)	0.017^{***}	(0.001)	0.017^{***}	(0.001)	0.013^{***}	(0.002)	0.013^{***}	(0.002)	0.013^{***}	(0.002)
# of HH members: primary industry	0.022	(0.026)	0.020	(0.026)	0.001	(0.029)	0.031	(0.070)	0.025	(0.070)	0.014	(0.078)
# of HH members: secondary industry	0.048^{*}	(0.026)	0.041	(0.026)	0.029	(0.026)	0.043	(0.042)	0.042	(0.041)	0.038	(0.045)
# of HH members: tertiary industry	0.210^{***}	(0.018)	0.205^{***}	(0.018)	0.199^{***}	(0.018)	0.146^{***}	(0.021)	0.141^{***}	(0.021)	0.126^{***}	(0.025)
land per capita in acres	0.077^{***}	(0.014)	0.079^{***}	(0.014)	0.080^{**}	(0.032)						
number of crops grown by HH	0.029^{**}	(0.013)	0.029^{**}	(0.013)	0.039^{**}	(0.017)						
index of economic infrastructure	0.085^{***}	(0.014)	0.054^{***}	(0.014)	0.055^{***}	(0.015)	0.045^{*}	(0.027)	0.011	(0.023)	-0.043	(0.048)
index of health infrastructure	0.037^{***}	(0.010)	0.034^{***}	(0.010)	0.031^{***}	(0.011)	0.042	(0.033)	0.067^{**}	(0.028)	0.116^{**}	(0.056)
zones included	Yes		Yes		Yes		No		No		No	
Chi2 (significance of agro-ecolog. zones)	262.79		275.54		297.09							
P-value of Chi2	0.00		0.00		0.00							
seasons included	Yes		Yes		Yes		Yes		Yes		Yes	
Chi2 (significance of seasonal effects)	7.51		6.66		7.01		6.67		16.22		39.25	
P-value of Chi2	0.06		0.08		0.06		0.08		0.00		0.00	
Chi2 (Contextual effects)			69.45		43.36				82.01		11.63	
P-value of Chi2			0.00		0.00				0.00		0.00	
Chi2 (overall significance)	5159.71		5274.86		1290709.86		1231.92		1349.89		79601.82	
P-value of Chi2	0.00		0.00		0.00		0.00		0.00		0.00	
Observations	10038		10038		10038		2233		2233		2233	

Notes: CE denotes contextual effects. HLM is a standard hierchical linear model. HT is Hausman-Taylor adaptation of the HLM model. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 4: Contextual effects (CE) of average years of schooling in a community

Table 5: Contextual effects (CE) across the first decile and the last decile

Variable	Rural		Urban	
	Bottom 10%	Top 10%	Bottom 10%	Top 10%
Comm. average of schooling of females	0.055***	-0.011	0.070*	0.063*
	(0.020)	(0.030)	(0.038)	(0.033)
	[2010]	[438]	[329]	[1144]
Comm. average of schooling of males	0.033*	0.026	0.050**	0.045*
	(0.018)	(0.025)	(0.022)	(0.026)
	[1759]	[609]	[275]	[544]

Notes: Deciles are for the corresponding household level variable. In square brackets are observations in each decile of a variable. Standard errors in parentheses, *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 6: Changes in average per capita expenditure following an additional year of schooling

	Mean	Female		Male	
		Within Household	Community	Within Household	Community
Rural	336.40	14.13	24.22	10.09	20.52
Urban	846.87	42.34	83.84	38.96	66.90

Notes: Over the survey period the exchange rate was Malawi Kwacha (MK) 150.80=1US$. The mean expenditures are population weighted.

Table 7: Contextual effects (CE) of maximum years of schooling in a community

Variable	Rural		Urban	
	HT CE	SE	HT CE	SE
HH max. years of schooling of females	0.037***	(0.002)	0.041***	(0.005)
HH max. years of schooling of males	0.029***	(0.002)	0.035***	(0.005)
Comm. max. of schooling of females	0.038**	(0.015)	0.072***	(0.009)
Comm. max. schooling of males	0.037**	(0.017)	0.057***	(0.016)

Notes: CE denotes contextual effects. HT is Hausman-Taylor adaptation of the hierchical linear model. Control variables (not shown) are the same as those in Table 4. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 8: Contextual effects (CE) of average years of schooling in a district

Variable	Rural		Urban	
	HT CE	SE	HT CE	SE
HH average years of schooling of females	0.038***	(0.002)	0.046***	(0.004)
HH average years of schooling of males	0.026***	(0.002)	0.041***	(0.004)
District average of schooling of females	0.042***	(0.001)	0.068*	(0.002)
District average of schooling of males	0.030***	(0.006)	0.070***	(0.007)

Notes: CE denotes contextual effects. HT is Hausman-Taylor adaptation of the hierchical linear model. Control variables (not shown) are the same as those in Table 4. Standard errors in parentheses. *** indicates significant at 1%; ** at 5%; and, * at 10%.