Early-Life Rainfall Shocks and Intergenerational Education Mobility in Malawi

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Abstract

The paper examines the relationship between intergenerational education mobility and children's rainfall shocks in the year of birth in Malawi. These rainfall shocks reflect exogenous reductions in household income. Survey data which is linked to rainfall data for the period 1958 to 1986 is used. The paper finds that birth-year rainfall shocks reinforce intergenerational educational mobility between mothers and their daughters only. The partial mother-daughter intergenerational coefficients of education are 0.344 and 0.392 for daughters affected and unaffected by a rainfall shock in their year of birth respectively. Rainfall shocks reinforce intergenerational educational immobility at the left tail of the education distribution while they reduce immobility at the right tail of the education distribution. The results are insensitive to a number of specification concerns including: usage of different rainfall shock thresholds based on the gamma distribution, alternative definitions of shocks which are not based on a distributional assumption and cover both droughts and floods, the timing of rainfall shocks, and mortality selection. A plausible interpretation of these findings is that given that poor families are less likely to have adequate shock mitigation strategies, early-life rainfall-related income shocks have a permanent and long-run effect of limiting equality of opportunity.

Keywords: Intergenerational Mobility; Rainfall Shocks; Malawi

1 Introduction

The level of intergenerational mobility in a society is an indicator of the degree of equality of economic opportunity. Equality of opportunity which entails that poor children should have the same opportunities for success as rich children is an underlying goal of society (Hertz et al., 2007; Black & Devereux, 2011; Checchi et al., 2013; Johnston et al., 2014; Ranasinghe, 2015; Azam & Bhatt, 2015; Daude & Robano, 2015; Azomahou & Yitbarek, 2016). A society in which a person's chances of success depend little on his or her family background is considered to have high social mobility or is called "a land of opportunity" (Bhalotra & Rawlings, 2013; Chetty et. al., 2014a).

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A number of cross-country or sub-national studies (Andrews & Leigh, 2009; Corak, 2013; Chetty et. al., 2014b) focusing on the developed world find a negative correlation between inequality and social mobility, and this relationship is called the "Great Gatsby curve". As argued by Corak (2013), inequality is inversely related to mobility because it shapes opportunity. Another channel through which inequality affects mobility is the passing of labor market outcomes to the succeeding generation by parental investment made in children's human capital. As inequality increases so does the gap in educational advantages that can be bought by richer and low-income parents for their children (Burtless and Jencks, 2003; Solon, 2004).

This paper focuses on intergenerational educational mobility as an indicator of social mobility. Intergenerational persistence of education disadvantage is a result of an interplay between nature and nurture. Nature involves a process of genetic inheritance as measured by the IQ (Anger & Heineck, 2010; Björklund et al. 2010). Parents endowed with high IQ may transfer this endowment to their offspring leading to persistence of education across generations. In contrast, nurture refers to external or environmental conditions such as the returns to education, the amount of time and economic investments of parents on a child's human capital accumulation (Black & Devereux, 2011; Bhalotra & Rawlings, 2013; Huang, 2013; Azomahou & Yitbarek, 2016).

Nurture conditions such as weather shocks in early life have irreversible long-run impacts on schooling (Maccini & Yang, 2009; Dercon & Porter, 2014; Shah & Steinberg, 2015; Duque et al., 2016). According to the "foetal origins hypothesis" or Barker's hypothesis (Barker 1992; Almond and Currie, 2011) adult outcomes are strongly influenced by experiences in the womb, in infancy and in early childhood. Hence, weather shocks in early life may reflect food inavailability at a critical period of life which may have permanent effects on education.

With respect to the intergeneration persistence of health outcomes, there is evidence that nurture conditions in early life such as birth-year improvements in maternal education, income and public health provision limit the intergeneration persistence of health outcomes (Bhalotra & Rawlings, 2013). In a similar vein, is the intergeneration persistence of education influenced by weather shocks in the year of birth? This paper brings together the literature on intergenerational educational mobility and the literature on the persistence of early life weather shocks. To the best of my knowledge, there is no study which has integrated the two strands of literature on the persistence of economic outcomes. Specifically, this paper closes this gap by assesing whether rainfall shocks in children's early-life moderate or enhance intergenerational persistence in educational attainment in Malawi.

Studying the possible interaction between early-life rainfall shocks and intergenerational educational mobility in a country like Malawi is even more relevant as such shocks are likely to be more pronounced in developinng countries (Currie and Vogl, 2013). Further to that, and in light of the prevailing global warming, rainfall shocks are likely to get more frequent and their intensity less predictable (Kovats et al., 2003; Cai et al., 2014). Moreover, IPCC (2014) projections indicate that in the absence of sufficient mitigation measures, climate change will "lead to high to very high risk of severe, widespread, and irreversible impacts globally" by the end of the century.

In addition to closing the knowledge gap on whether rainfall shocks interact with intergenerational educational persistence, this paper builds on and makes two other contributions to the literature. The first contribution is that by studying intergenerational mobility in Malawi, this paper adds to the literature on intergenerational educational mobility in Africa. As noted by Azomahou & Yitbarek (2016), literature on intergenerational educational mobility in Africa is scarce, and that the little that is there has tended to focus on South Africa (e.g. Nimubona & Vencatachellum (2007), Branson et al. (2012), Kwenda et al. 2015).

Second, this paper contributes to the literature on gender differences in education attainment. For instance, Maccini & Yang (2009) find that rainfall shocks have a gender-differentiated effect on education whereby a 20% increase in local rainfall in the year of birth is associated with a 0.22-year increase in education attainment for women in rural Indonesia, and that birth-year rainfall has no long-run effect on men's schooling. In this paper, I look at how the interaction between intergenerational educational persistence and birth-year rainfall shocks varies with the gender of the child. Precisely, the paper provides interaction estimates for the following parent-child pairs: daughters-mothers, sons-mothers, daughters-fathers, and sons-fathers.

In an agrobased economy such as Malawi, rainfall shocks essentially capture exogenous variation in household income (Hidalgo et al., 2010; Burke et al., 2014; Flatø et al., 2016). Thus, extreme rainfall reflects exogenous reductions in household income. The direction of the interaction between birth-year exogenous reductions in income and parental education, if it exists cannot be determined *a priori*. There are two possible competiting hypotheses as to the sign of the interaction effect.

The first hypothesis is that the interaction effect is positive such that intergenerational educational immobility is more enhanced for children who experienced birth-year decreases in household income. This would hold if rainfall shocks cause general equilibrium effects which reduce real wages leading to income and substitution effects (Rosales-Rueda, 2016). For the interaction effect to be positive, the substitution effect has to dominate following the fall in wages triggering a decrease in the opportunity cost of time, which in turn compels mothers to substitute their time away from labor activities to time investments in childcare.

The second hypothesis is that the interaction is negative, implying that reductions in birth-year income attenuate the transmission of education from parents to children. In this case, a reduction in birth-year income would diminish the strength of the parent-child schooling association through limiting the ability of parents to purchase and provide better nutrition and childcare (Maccini & Yang, 2009; Black & Devereux, 2011). In the presence of general equilibrium effects, a positive interaction would also emerge if the income effect outweighs the substitution effect (Rosales-Rueda, 2016).

The remainder of this paper is structured as follows. A description of the data and variables used in the study is given in Section 2. Section 3 presents the empirical strategy. This is followed by a discussion of empirical results in Section 4. Finally, Section 5 discusses the results and draws conclusions.

2 Data and Variables

2.1 Individual Level Data

Individual data on parents and their offspring are taken from the Third Integrated Household Survey (IHS3). The IHS3 is statistically designed to be representative at national, district, urban and rural levels. The survey was conducted by the National Statistical Office, and it was fielded from March 2010 to March 2011. It 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 56409 individuals within the households were covered; 10096 (representing 17.9%) in urban areas, and 46313 (representing 82.1%) in rural areas. It also has data on children and their parents' education irrespective of whether parents were alive or, if alive were co-resident. A key merit of this data is that parental education data is retrospective, and therefore one does not need to impose a co-residence condition to measure education mobility. Co-residence in addition to significantly reducing the analysis sample can lead to endogenous sample selection (Francesconi & Nicoletti, 2006; Azam & Bhatt, 2015).

The government of Malawi has since 1994 been splitting some of the districts to create new ones. Currently there are 28 districts, and since this paper uses birth year rainfall which corresponds to one's district of birth from before 1994, the new districts are merged back into the old ones to end up with 24 districts.

2.2 Rainfall Data

The paper uses rainfall data taken from the Watch Forcing Data (WFD) prepared by Weedon et al. (2010). The WFD data comprises of subdaily, regularly gridded, half-degree resolution, meteorological forcing data. The data are based on interpolated weather station data and have a global coverage over land areas from 1958 to 2001. The IHS3 data includes the district of birth and year of birth of each household member, and I use these two variables to merge the individual level data with the rainfall data.

I match a total of 41 weather stations with the 24 birth districts in IHS3. For districts with two or more weather stations, a simple average of the weather stations is used. Malawi's climate can be characterised as tropical wet and dry, also known as savanna. The main rain season is from November and the dry season is from May to October (Ngongondo et al. 2011). In addition to the wet-season rainfall which comes in the summer, some areas experience sporadic winter rains locally called *chiperoni* between May and August (Ngongondo et al. 2011).

To generate rainfall in one's year of birth, I only use rainfall corresponding to a complete wet season from November to April (rather than calendar year rainfall or *chiperoni*). Crop production in Malawi is predominantly rainfed, and it is the wet season rainfall which is closely related to crop production. I identify each individual's birth-year wet season by using their month of birth. Rainfall in one's year of birth is then defined as the sum of rainfall in one's wet season in his/her district of birth i.e. the six consecutive months from November to April.

Although the oldest respondent in the IHS3 was born in 1900, I restrict the merged sample of children to the period 1958-1986. The left-end restriction of 1958 is purely driven by the availability of rainfall data. The 1986 birth cohort is the last cohort such that the youngest children are 25 or 26 at the time of the survey in 2010/11. Since most Malawians complete the schooling cycle in their mid-20s, this restriction is useful as it ensures that I only focus on those who have completed schooling.

The working sample has 11050 children with nonmissing parental and own education data. Of this total, 5079 are female (representing 46.0%) and 5971 are male (representing 54%). Figure 1 shows the number of children by year of birth in the final sample. As would be expected, the number of children progressively increases overtime. It ranges from a low of 171 in 1958 to a high of 746 in 1982.The number of sons is larger than the number of daughters up to the early 1980s, and a reverse pattern is observed thereafter.

Three parental education variables are used; a father's and a mother's years of schooling, and parental years of schooling defined as the average of a father's and a mother's years of schooling. Figure 2 shows a visual depiction of the evolution of average years of schooling of children (daughters and sons) and their parents across the children's years of birth. Over the period 1958-1986, there is a slight upward trend in years of schooling for parents and their offspring. Compared to their parents, and regardless of gender, children have on average more years of. schooling. Furthermore, there is a discernible gender difference in average years of schooling; across the years of birth, sons have higher average years of schooling than daughters, and fathers have more years of schooling than mothers.

As illustrated by Figure 3, average rainfall has over the study period been fairly volatile. Average rainfall reached a low of about 850mm in the mid-1950s and a high of about 1400 in the mid-1970s. These highs and lows correspond to years of drought and floods respectively which Malawi experienced. This observed volatility in rainfall in Malawi is not necessary a unique feature of the study period, 1958-1986. Lewin et al. (2012) notes that Malawi has highly variable rainfall with 31 droughts and floods occurring over the period 1960-2009.

To capture birth-year rainfall shocks which are uncorrelated with local characteristics, I follow Burke et al. (2014) and Flatø et al. (2016) and transform the birth year rainfall levels into relative rainfall by using a cumulative gamma distribution. This transformation ensures that in each year, each district receives a value which reflects the probability of having a rainfall at that level or below in that particular district. A rainfall shock is then defined as a dummy variable taking the value one if the cumulative gamma distribution of rainfall falls below 0.25 and zero otherwise.

The rainfall shock variable should by construction be random and orthogonal to other confounding local characteristics. The reason for this is that rainfall shocks at given district of birth are defined relative to that district's historical rainfall distribution, and the same percentile threshold instead of an absolute threshold to define a shock is adopted in each location (Burke et al., 2014; Flatø et al., 2016). This in turn implies that each birth-district-birth-year combination has a 25% chance of experiencing a shock. As a robustness check, I re-define rainfall shocks using alternative shock thresholds, and also re-define a rainfall shock in standard deviation units (Hidalgo et al., 2010).

3 Empirical Strategy

The regression based measurement of intergenerational persistence of education typically involves regressing the schooling of children on their parental schooling (Hertz et al., 2007; Checchi et al., 2013; Huang, 2013; Ranasinghe, 2015; Azam & Bhatt, 2015). In keeping with this approach, I use the following linear regression to examine the possible interrelationship between intergenerational transmission of education and rainfall shocks in the year of birth

$$s_{ij}^{c} = \beta_1 + \beta_2 s_{ij}^{p} + \theta y_{ij} + \delta s_{ij}^{p} y_{ij} + F + T + M + \varepsilon_{ij} \tag{1}$$

where, β_1 is an intercept, s_{ij}^{c} is years of schooling of child i born in district j, s_{ij}^{p} is his/her parental years of schooling with slope coefficient β_2, y_{ij} is a rainfall shock dummy in the year of birth, and θ is the corresponding coefficient, F, T and M are district of birth, year of birth and month of birth fixed effects respectively, and $\varepsilon_{ij} \sim N(0, \sigma_{\varepsilon}^{2})$ is an idiosycratic error term. The coefficient β_2 measures intergenerational persistence of education i.e. intergenerational educational immobility. If child schooling is not influenced by parental schooling then β_2 is zero i.e. there is education mobility. Thus, a higher value of β_2 implies greater intergenerational persistence (or lower mobility) in education. Alternatively, $1-\beta_2$ is a measure of intergenerational educational mobility.

The focus of this paper is on whether there is any association between birth-year rainfall shocks and intergenerational educational mobility; in this regard, the interaction coefficient δ is the parameter of interest. For instance, a rejection of the null hypothesis $H : \delta = 0$ implies that intergenerational educational mobility depends on birth-year rainfall shocks. The sign of δ indicates the nature of the dependence. The sign of β_2 is expected to be positive (Ranasinghe, 2015; Azam & Bhatt, 2015; Daude & Robano, 2015), and this means that if δ is also positive then birth-year rainfall shocks and intergenerational educational persistence are complementary i.e. birth-year rainfall shocks reduce education mobility. In contrast, if δ is negative, then rainfall shocks in the year of birth diminish intergenerational educational persistence i.e. rainfall shocks increase education mobility.

Intergenerational education mobility as measured by $1 - \beta_2$ masks interesting detail about intergenerational mobility across the entire joint distribution of parental and child schooling (Black & Devereux, 2011; Azam & Bhatt, 2015). To get a fuller picture of the pattern of the possible dependence between education mobility and rainfall shocks I also use intergenerational mobility matrices. For children that experienced a rainfall shock in the year of birth and those that did not respectively, I compute the mobility matrix $\mathbf{P} = [p_{ij}]$, where i denotes a parent's education category and j denotes the education category of the child. p_{ij} captures the probability of a parent with education category i having an offspring with education category j.

The interpretation of the probabilitties is as follows: larger values for p_{ii}, the principal diagonal elements, indicate lower education mobility while larger values for p_{ij}, the off diagonal items, entail higher education mobility. To construct these matrices, I use four schooling categories; no education, primary education, secondary education, and tertiary education. A comparison of the probabilities across the different education categories by rainfall shock status provides some insights into how the interaction between rainfall shocks and mobility varies across different levels of education attainment.

4 Results

Table 1 shows results from an OLS regression of the interaction between between intergenerational educational mobility and birth-year rainfall shocks. For these results no distinction is made between sons and daughters and how the intergenerational persistence of education depends on rainfall shocks.The results in Columns 1, 3, 5 do not control for month of birth, year of birth, and district of birth fixed effects while Columns 2,4, 6 include the three sets of fixed effects. The coefficients on parental years of schooling which is a combination of mother's and father's schooling are positive and statistically different from zero. This means that there is significant transmission of education from parents to their children. The inclusion of the three sets of fixed effects reduces the size of this intergenerational coefficient, but it does not lead to a loss of statistical significance.

Father's and mother's schooling separately are statistically significantly related to the schooling of their offspring. Here again the inclusion of fixed effects only affects the sizes of the intergenerational coefficients but does not alter their statistical significance. Henceforth, the rest of the interpretation is based on the results which account for fixed effects. The results indicate that the intergenerational coefficients for maternal schooling are larger than those for paternal schooling. This difference is statistically significant with a 95% confidence interval of [0.021, 0.129].

All this suggests that the intergenerational persistence of education is more pronounced between mothers and their children. This finding is in conformity with the literature which suggests that the effect of mother's education on children's educational attainment is greater than that of fathers (Black & Devereux, 2010; Branson et al., 2012; Kwenda et al., 2015; Ranasinghe, 2015; Azomahou & Yitbarek, 2016). This is primarily explained by the fact that educated mothers may be more likely to affect parental time allocation and parental productivity in child enhancing activities (Huang, 2013).

The preceeding results point to the existence of intergenerational educational immobility in Malawi. The focus of this paper is to examine whether this persistence depends on birth-year rainfall shocks. The key question to be answered is: Do rainfall shocks in a child's year of birth strengthen or diminish intergenerational transmission of educational attainment? The results in Table 1 help in answering this question; they include interaction coefficients between rainfall shocks and parental schooling, father's schooling, and mother's schooling.

The interaction coefficients are all negative. The results show that intergenerational educational immobility in Malawi is influenced by rainfall shocks, however, this interrelationship depends on whether one is looking at paternal or maternal schooling. When the aggregated parental schooling is interacted with rainfall shocks, the interaction coefficient is statistically significant in the model without fixed effects only; suggesting that the significance is confounded by the exclusion of the fixed effects. Moreover, the results show that the interaction effect between father's schooling and rainfall shocks is statistically indistinguishable from zero. father-child intergenerational persistence of education

The results however reveal that there is a statistically significant interaction between mother's schooling and rainfall shocks. The negative sign of the interaction coefficient implies that birth-year rainfall shocks decrease rather than strengthen the intergenerational transmission of educational attainment from mothers to their children. Thus, it is the transmission of mother's schooling to their offspring which is impacted by birth-year rainfall shocks. Precisely, and holding other factors constant, the mother-child intergenerational coefficient of education is 0.316 for those children who experienced a rainfall shock in their year of birth and it is 0.359 for those children who had no birth-year rainfall shock.

This finding raises an inevitable and interesting question: does the interaction betwen mother's schooling and rainfall shocks depend on the gender of the child? Where precisely is this interaction betwen mother's schooling and rainfall shocks? Is it between mothers and sons or mothers and daughters or both? I disaggregate the analysis by gender of children, and the results for this analysis are displayed in Table 2. It should first be pointed out that a comparison of the results in Columns 5 and 6 shows that maternal schooling has a larger effect in shaping the educational outcomes of daughters ($\hat{\beta}_2 = 0.392$) than sons ($\hat{\beta}_2 = 0.327$).

With respect to the interactions, the results indicate that the interaction between rainfall shocks and maternal schooling depends on the gender of the child. Specifically, there is a negative and statistically significant interaction between mother's schooling and birth-year rainfall shocks experienced by daughters (Column 6). In contrast, the coefficient is negative for sons (Column 5) but it is not statistically significant. This implies that birth-year rainfall shocks decrease the intergenerational transmission of education from mothers to their daughters but not to their sons. The partial mother-daughter intergenerational coefficients of education are 0.344 and 0.392 for daughters affected and unaffected by a rainfall shock in their year of birth respectively. This gendered effect of birth-year rainfall shocks is in agreement with Maccini & Yang (2009) who found that women with 20% higher rainfall in their year and location of birth are complete 0.22 more grades of schooling in rural Indonesia, and that birth-year rainfall has a statistically insignificant effect on men's schooling.

The above results do not show the nature of the interaction between rainfall shocks and intergenerational persistence of mother's education and daughters education across the entire distribution of education attainment. A fuller picture of the pattern of the interaction between education mobility and rainfall shocks is reported in.Table 3. The table shows an intergeneratonal mobility matrix for those children who experienced a rainfall shock in their year birth and those who did not. The rainfall shock threshold used is the 25th percentile. Each row of the table shows the education attainment of the daughter while columns indicate the education attainment of the mother.

Looking at the probabilities across the principal diagonal- indicators intergenerational educational persistence- the results indicate that regardless of shock status, intergenerational educational persistence is more pronounced at the top and bottom ends of the education distribution. The principal diagonal probabilities are in the neighbourhood of 75% for both no education and tertiary education while they as low as 13.3% for the intermediate levels of education.

The results reveal some differences in the effect of rainfall shocks across the distribution of education. First, the effect in terms of direction of rainfall shocks is different for the lower and upper tails of the education distribution. Rainfall shocks reinforce intergenerational educational immobility for daughters at the bottom end of the education distribution while they diminish immobility at the top end of the education distribution. Precisely, for daughters who experienced a rainfall shock in their year of birth and those who did not, 77.6% and 76.5% respectively had no education just like their mothers. In contrast, 77.8% of mothers with tertiary education had daughters with tertiary education who had a birth-year rainfall shock while the corresponding probability is 78.3% for daughters who did not experience a birth-year rainfall shock.

Second, although intergenerational educational immobility is highest at the two tails of the education distribution, rainfall shocks in the year of birth have the largest effect in diminishing intergenerational educational immobility with respect to primary education, and the effect is lowest for tertiary education. The results show that the principal diagonal probabilities for primary education are 13.3% and 20.7% for daughters who experienced a birth-year rainfall shock and those who did not respectively. The corresponding figures for tertiary education are respectively 77.8% and 78.3%. This means that rainfall shocks reduce intergenerational educational immobility by 35.7% for primary education and by 0.6% for tertiary education.

4.1 Robustness Checks and Potential Mechanisms

I subject the principal result that rainfall shocks in the year of birth reduce intergenerational persistence between mother's schooling and daughter's schooling to a number of robustness checks. I also discuss some potential pathways behind the significant interaction. The paper has used rainfall as an indicator of variation in income. I check the relevance of this by running regressions of maize yield measured in metric tonnes per hectare in the district and year of birth on corresponding average rainfall. Similar to many African countries, maize is a primary staple crop in Malawi, and accounts for more than two-thirds of caloric availability (Ecker & Qaim, 2011). It is the crop grown by the majority of smallholder farmers, and the best direct indicator of incomes especially rural incomes (Burke et al., 2014). The maize yield data is compiled from crop production data from the Ministry of Agriculture and Food Security. For each district and year, the maize yield is calculated as a total of local maize, hybrid maize, and composite maize. The maize data runs from 1984 to 1986; I then use year of birth and district of birth to link this data to the IHS3 and rainfall data. The final sample has 1309 children.

Table 4 contains regression results of the relationship between maize yield and rainfall. Separate regression results for rural and urban areas are also included. The regressions include district and year of birth fixed effects. Rainfall has the expected positive effect on maize yield. However, this effect is only statistically significant in the rural regression. This means that rainfall is a good measure of income variation in rural areas. Consequently, one would therefore expect that in rural areas where rainfall significantly affects incomes, the interaction between rainfall shocks and mother's schooling for daughters would be significant and more pronounced. To check this, I re-estimated the interaction between rainfall shocks and mother's schooling separately for rural and urban areas. Results are presented Table 5. The results indicate that the interaction effect is statistically different from zero in the rural regression only. This suggests that it is only in rural areas where rainfall shocks diminish intergenerational educational persistence between mothers and daughters.

Another concern with the results is that the rainfall shock threshold is arbitrarily chosen to be the 25th percentile, and that this choice might be driving the results. To address this concern, I vary the cut-off for shock definition in increments of 5% between the 20th and the 50th percentile. The estimated interaction coefficients for each percentile and their corresponding 95% confidence interval bands are depicted in Figure 4. The point estimates for the different thresholds are not only statistically significant, but they are close to the 25th percentile shock definition adopted in this paper. Another noteworthy thing is that there is a slight decline in the size of the interaction coefficient as the definition of a shock becomes less stringent i.e. moving from the 20th to the 50th percentile.

Table 6 shows that the insensitivity of the results to choice of shock threshold also holds when education mobility matrices are used instead. In this instance, the results confirm the earlier findings regarding the effect of rainfall shocks across the entire distribution of education. As a matter of fact, as one transitions from the 20th to the 50th percentile, the results for the different thresholds are almost identical. For all thresholds, rainfall shocks reinforce intergenerational educational immobility at the left tail of the education distribution while they reduce immobility at the right tail of the education distribution. Furthermore, for all thresholds, birth-year rainfall shocks have the largest effect in reducing intergenerational educational immobility between mothers and daughters for primary education.

The key result of this paper has been based on rainfall shocks derived from a transformation of birth-year rainfall into relative rainfall by using the cumulative gamma distribution. Morever, the shocks as defined here essentially reflect droughts and not floods. To ensure that the result is not driven by the gamma transformation, and the shocks cover both droughts and floods, I use absolute and squared standardized rainfall as proposed by Hidalgo et al. (2010). The absolute and squared standardized rainfall are respectively generated as $z_{ij} = \left|\frac{y_{ij}-\bar{y}}{s}\right|$ and $z'_{ij} = \left(\frac{y_{ij}-\bar{y}}{s}\right)^2$; where birth-district-birth-year rain observations, y_{ij} are standardized by the mean, $\bar{y}$ and standard deviations, s of the rain data for the period 1958-1986.

Using absolute values and squaring addresses the problem that both drought and flooding are negatively correlated with agricultural income (Hidalgo et al., 2010). The results for the re-defined variables are shown in Table 7. Just like before, the interaction between mother's schooling and rainfall shocks as measured by absolute and squared deviations of rainfall is negative and statistically significant. Thus, the key result of this paper is insensitive to an alternative definition of rainfall shocks.

Another specification concern is that it is not necessarily rainfall shocks in the year of birth that matter (Mancini & Yang, 2009; Flatø et al., 2016). Rainfall can be serially correlated over time, implying that rainfall in some year before or after the year of birth has the actual impact on intergenerational educational mobility. Consequently, the measured interaction effect between mother's schooling and birth-year shocks could simply be picking up the omitted past and future rainfall shocks. To alleviate this concern, I re-estimated an augmented model with two additional interaction variables namely; an interaction between mother's schooling and rainfall shocks just prior to birth i.e. rainfall shocks *in utero,* and an interaction between mother's schooling and rain shocks in the second year of birth.

The results for this sensitivity check are reported in Table 8. The interaction coefficient between birth-year rainfall shocks and mother's schooling is still significant, however, there is no statistically significant interaction between rainfall shocks *in utero* and in the second year of life and mother's schooling. Thus, the significant negative interaction between mother's schooling and birth-year rainfall shocks found earlier is not necessarily a result of rainfall shocks which are serially correlated overtime.

Finally, selection effects might confound the key finding of this paper. The analysis in this paper includes children who were alive in 2010/11, at the time the IHS3 was fielded. This might raise selection concerns if birth-year rainfall shocks influence the likelihood of a child surviving through 2010/11. To allay this concern about this possible mortality selection, I estimated two linear regressions of male and female farmers' birth-district and birth-year cohort sizes on early life maize yields. The results are reported in Table 9, and they are disaggregated by gender. Gender disaggregation is critical because as found by Waldron (1983) boys are more vulnerable than girls to dying in childhood. Consequently, one would expect mortality selection to be more evident among males than females. The results indicate that there is no statistically significant relationship between rainfall shocks and cohort sizes for male and female children.

The results indicate that rainfall is a good measure of crop income variation in rural areas, and that it is in rural areas where the interaction between birth-year rainfall shocks and mother's schooling for daughters is significant. As argued by Hoynes et. al.(2016), causal mechanisms through which early-life events have long-run effects are best understood for nutrition. Consequently, these reductions in birth-year rainfall-related income whether through droughts or floods would limit the capacity of parents to purchase and provide better nutrition and also the time allocation of the parent (especially mothers) in child-enhancing activities (Maccini & Yang, 2009; Black & Devereux, 2010).

Rainfall shocks as a direct channel would also affect food availability which would ultimately affect child nutrition. This early-life nutritional deprivation can lead to poor educational and socioeconomic outcomes. As pointed out by Case and Paxson (2006) the relationship works through two channels; a) through impairments of cognitive ability due to early-life malnutrition that harms school success and, subsequently, labor market outcomes, and, b) through early life malnutrition which translates into poor child health which in turn reduces both school attendance and attainment.

Rainfall shocks can also lead to general equilibrium effects such as local changes in commodity prices and real wages, and these can in turn trigger competing income and substitution effects (Rosales-Rueda, 2016). The income effect would arise from a decrease in wages which would entail tighter budget constraints and fewer resources to invest in children. In contrast, the substitution effect would prevail if the decline in wages leads to a decrease in the opportunity cost of time, which in turn compels mothers to substitute their time away from labor activities to time investments in childcare. The fact that the strength of the association between mother-daughter schooling is reduced by birth-year income reductions suggests that if the indirect effect exists it works through the income effect.

5 Conclusions and Implications

The paper has examined the relationship between intergenerational educational mobility and children's rainfall shocks in the year of birth in Malawi. Survey data which is linked to rainfall data for the period 1958 to 1986 is used. I have used rainfall shocks defined from a cumulative gamma distribution to ensure that the shocks are random and orthogonal to other confounding local characteristics. The paper has found that there is significant intergenerational persistence of education between parents and their children, and that this persistence depends on rainfall shocks experienced in the children's year of birth. This interaction however manifests itself in a gendered way.

There is no significant interaction between sons' and daughters' birth-year rainfall shocks and father's schooling. Furthermore, no significant interaction exists between sons' birth-year rainfall shocks and mother's schooling. However, it has been found that there is a negative and statistically significant interaction between mother's schooling and birth-year rainfall shocks experienced by daughters. All this means that childhood rainfall shocks reinforce intergenerational educational mobility between mother's and their daughters.

Education mobility matrices further confirm this finding, and indicate that rainfall shocks reinforce intergenerational educational immobility at the left tail of the education distribution while they reduce immobility at the right tail of the education distribution. For all thresholds, birth-year rainfall shocks have the largest effect in reducing intergenerational educational immobility between mothers and daughters for primary education.

There are two possible interpretations of the results. First, and on the face of it, birth-year rainfall shocks are a good thing as they reduce the transmission of family disadvantage from mothers to their daughters. The second interpretation is that rainfall shocks in the year birth are a bad thing to the extent that they can be associated with reductions in food availability, in household income and in time allocation and the productivity of the parent in child-enhancing activities (Maccini & Yang, 2009; Black & Devereux, 2010). Given the above evidence that the impact of rainfall is felt in rural areas only and at the high end of the education distribution, this latter interpretation seems more plausible, as these findings most likely reflect an inability by household to mitigate against shocks.

The first policy implication of the findings is that they point the existence of partial consumption smoothing among households in Malawi. The fact that temporary shocks in early life have permanent intergenerational effects indicates that households have limited smoothing ability possibly arising from a lack of mitigation strategies such as formal and informal support networks (Dercon & Hoddinot, 2003; Islam & Maitra, 2012). From a policy perspective, as shown by Islam & Maitra (2012), microcredit organizations and microcredit can play an insurance role to mitigate against such shocks. Second, the limited capacity of households to mitigate against birth-year rainfall shocks for infant girls also provides additional evidence in support of interventions such as weather insurance and the development and provision of drought resistant crop varieties.

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Figure 1: Number of children, 1958-1986

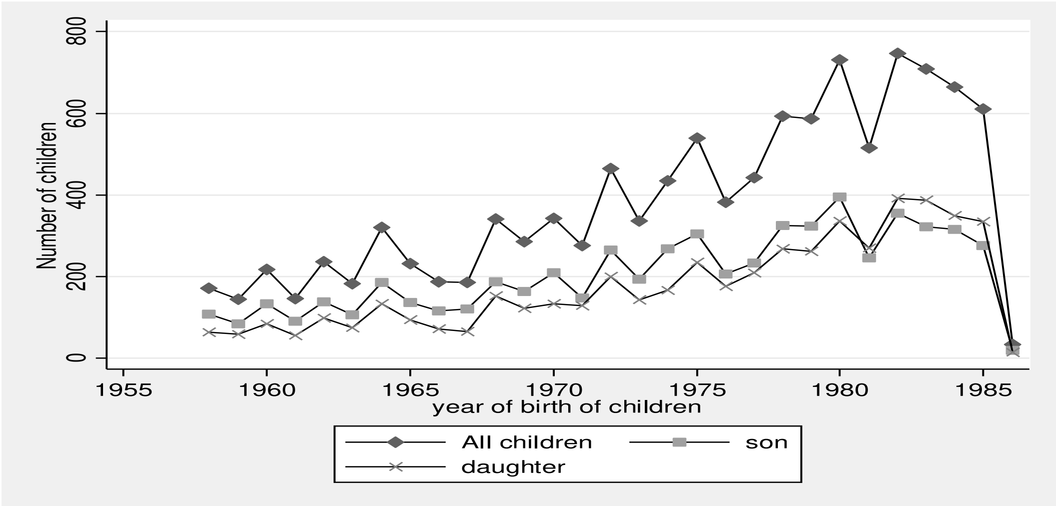

Figure 2: Evolution of average years of schooling, 1958-1986

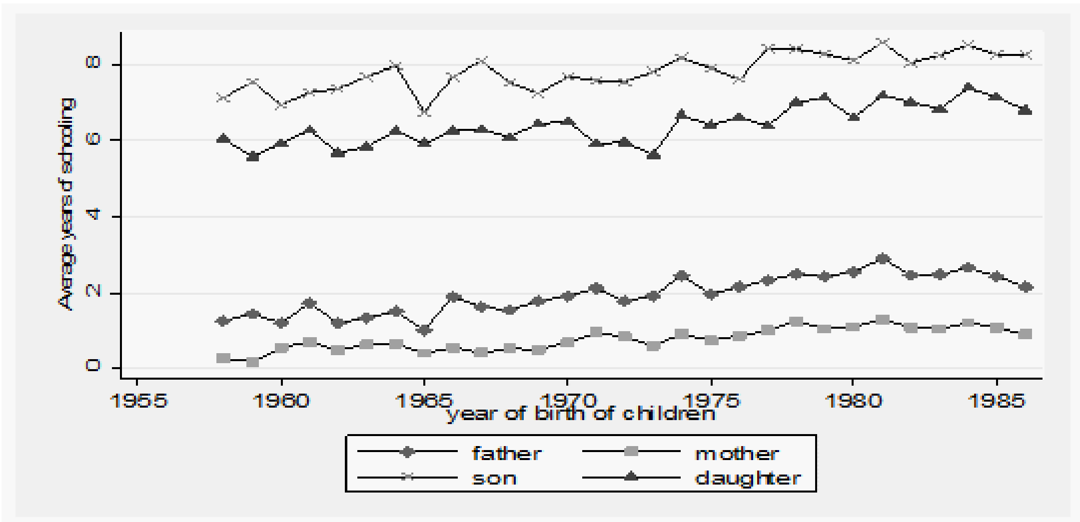

Figure 3: Evolution of average rainfall, 1958-1986

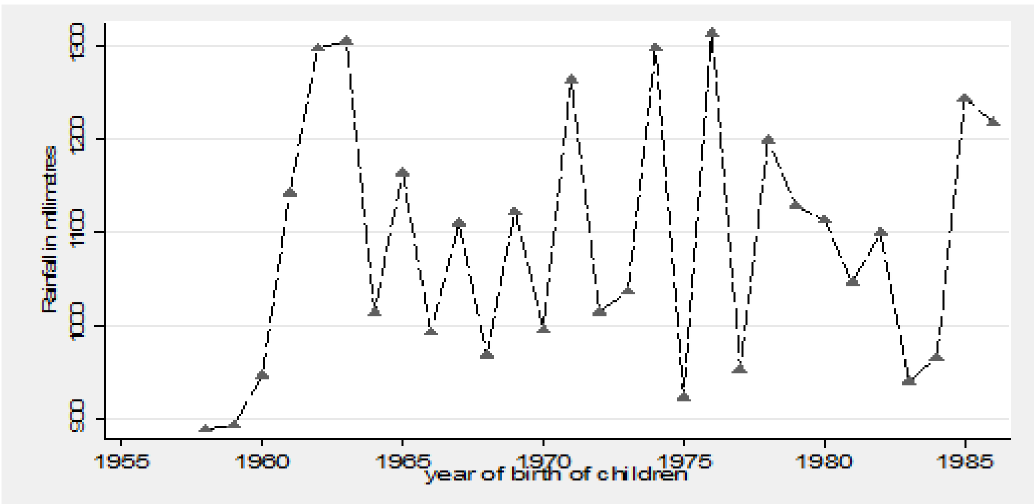

Table 1: Results for parental education with no child gender disaggregation

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Parental years of schooling	0.461***	0.408***				
	(0.017)	(0.019)				
Father's years of education			0.325***	0.284***		
			(0.015)	(0.016)		
Mother's years of education					0.415***	0.359***
					(0.021)	(0.022)
Rain shock in first year × parental years of schooling	-0.051**	-0.032				
	(0.019)	(0.020)				
Rain shock in first year × father's years of education			-0.035	-0.020		
			(0.021)	(0.015)		
Rain shock in first year × mother's years of education					-0.061**	-0.043**
					(0.024)	(0.019)
Month of birth fixed effects	No	Yes	No	Yes	No	Yes
Year of birth fixed effects	No	Yes	No	Yes	No	Yes
District of birth fixed effects	No	Yes	No	Yes	No	Yes
R-Squared	0.17	0.23	0.16	0.22	0.11	0.18
Observations	11050	11050	11050	11050	11050	11050

Notes: The dependent variable is years of schooling of children. Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25. In parentheses are standard errors clustered at the district level. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 2: Results for parental education with child gender

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Sons	Daughters	Sons	Daughters	Sons	Daughters
Parental years of schooling	0.379***	0.433***				
	(0.018)	(0.023)				
Father's years of education			0.264***	0.301***		
			(0.015)	(0.021)		
Mother's years of education					0.327***	0.392***
					(0.024)	(0.025)
Rain shock in first year × parental years of schooling	-0.014	-0.037				
	(0.024)	(0.023)				
Rain shock in first year × father's years education			-0.004	-0.027		
			(0.020)	(0.018)		
Rain shock in first year × mother's years education					-0.028	-0.048*
					(0.027)	(0.025)
Month of birth fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year of birth fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
District of birth fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.22	0.29	0.21	0.27	0.18	0.23
Observations	5971	5079	5971	5079	5971	5079

Notes: The dependent variable is years of schooling of children. Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25. In parentheses are standard errors clustered at the district level. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 3: Transition matrix of mother's and daughter's education by shock status

	Rainfall Shock				No Rainfall Shock			
	none	primary	secondary	tertiary	none	primary	secondary	tertiary
none	77.58	42.17	21.31	0.00	76.45	33.51	12.31	0.00
primary	10.86	13.25	14.75	11.11	10.33	20.74	10.00	0.00
secondary	10.52	38.55	49.18	11.11	12.14	37.23	52.31	21.74
tertiary	1.04	6.02	14.75	77.78	1.08	8.51	25.38	78.26

Notes: The column and rows represent mothers and daughters respectively. Each cell ij represents the probability of a daughter with education level i having a mother with education attainment level j. Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25.

Table 4: Relevance of rainfall as a source of variation in income

Variable	All	Rural	Urban
Rainfall	0.859***	1.037***	0.554
	(0.137)	(0.154)	(0.496)
Year of birth fixed effects	Yes	Yes	Yes
District of birth fixed effects	Yes	Yes	Yes
R-squared	0.98	0.97	0.99
Observations	1309	957	352

Notes: The dependent variable is maize yield in tonnes per hectare in the district and year of birth. Rainfall is average rainfall in the district and year of birth in millimitres. In parentheses are robust standard errors. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 5: Rural and urban interactions between rainfall shocks and mother's schooling

Variable	Daughter's Years of Schooling	
	Rural	Urban
Mother's years of education	0.346***	0.330***
	(0.055)	(0.023)
Rain shock in first year × mother's years of education	-0.105*	-0.012
	(0.060)	(0.025)
Month of birth fixed effects	Yes	Yes
Year of birth fixed effects	Yes	Yes
District of birth fixed effects	Yes	Yes
R-Squared	0.13	0.26
Observations	3757	1322

Notes: Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25. In parentheses are standard errors clustered at the district level. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Figure 4: Interactions between different shock thresholds and mother's years of schooling

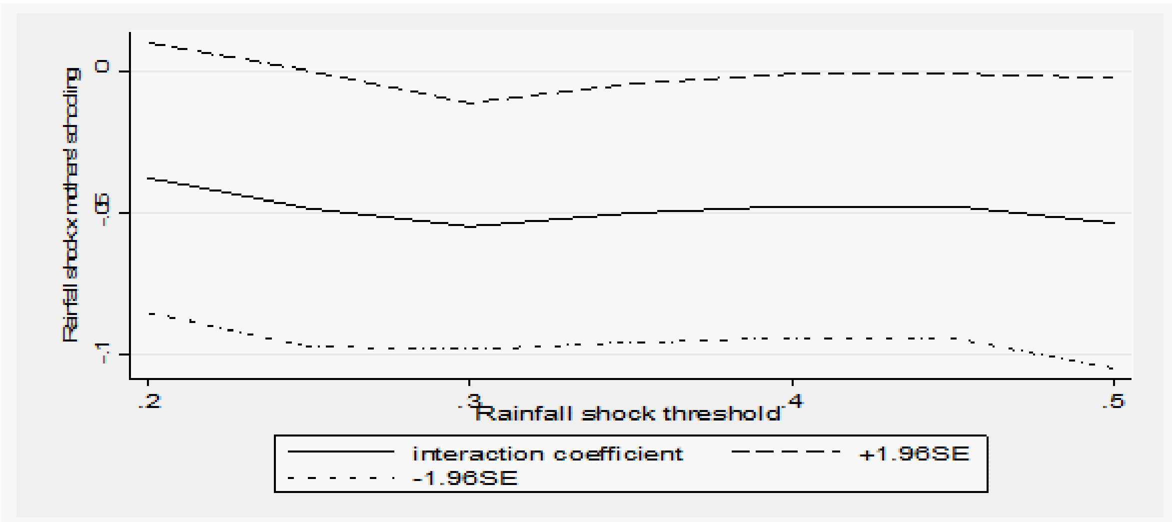

Table 6: Transition matrices of mother's and daughter's schooling for different shock thresholds

	Rainfall Shock				No Rainfall Shock			
	none	primary	secondary	tertiary	none	primary	secondary	tertiary
Threshold=0.5								
none	77.18	41.30	19.70	0.00	76.60	33.52	12.80	0.00
primary	11.19	11.96	16.67	11.11	10.13	21.79	8.80	0.00
secondary	10.56	38.04	50.00	11.11	12.20	37.43	52.00	21.74
tertiary	1.07	8.70	13.64	77.78	1.07	7.26	26.40	78.26
Threshold=0.45								
none	76.83	40.45	19.70	0.00	76.79	34.07	12.80	0.00
primary	11.33	12.36	16.67	11.11	10.07	21.43	8.80	0.00
secondary	10.74	38.20	50.00	11.11	12.08	37.36	52.00	21.74
tertiary	1.10	8.99	13.64	77.78	1.05	7.14	26.40	78.26
Threshold=0.40								
none	77.04	40.45	19.70	0.00	76.69	34.07	12.80	0.00
primary	11.25	12.36	16.67	11.11	10.12	21.43	8.80	0.00
secondary	10.66	38.20	50.00	11.11	12.11	37.36	52.00	21.74
tertiary	1.05	8.99	13.64	77.78	1.08	7.14	26.40	78.26
Threshold=0.35								
none	77.18	41.38	20.63	0.00	76.62	33.70	12.50	0.00
primary	11.01	12.64	15.87	11.11	10.25	21.20	9.38	0.00
secondary	10.81	37.93	49.21	11.11	12.03	37.50	52.34	21.74
tertiary	1.00	8.05	14.29	77.78	1.10	7.61	25.78	78.26
Threshold=0.30								
none	77.27	42.35	20.97	0.00	76.59	33.33	12.40	0.00
primary	10.99	12.94	14.52	11.11	10.26	20.97	10.08	0.00
secondary	10.72	37.65	50.00	11.11	12.06	37.63	51.94	21.74
tertiary	1.02	7.06	14.52	77.78	1.09	8.06	25.58	78.26
Threshold=0.25								
none	77.58	42.17	21.31	0.00	76.45	33.51	12.31	0.00
primary	10.86	13.25	14.75	11.11	10.33	20.74	10.00	0.00
secondary	10.52	38.55	49.18	11.11	12.14	37.23	52.31	21.74
tertiary	1.04	6.02	14.75	77.78	1.08	8.51	25.38	78.26
Threshold=0.20								
none	77.63	42.68	20.00	0.00	76.45	33.33	12.98	0.00
primary	11.01	12.20	15.00	11.11	10.27	21.16	9.92	0.00
secondary	10.36	39.02	50.00	11.11	12.18	37.04	51.91	21.74
tertiary	1.01	6.10	15.00	77.78	1.10	8.47	25.19	78.26

Notes: The column and rows represent mothers and daughters respectively. Each cell ij represents the probability of a daughter with education level i having a mother with education attainment level j. Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below a given threshold.

Table 7: Interaction between standardized rainfall and mother's schooling

Variable	Daughter's Years of Schooling	
	Absolute	Squared
Mother's years of education	0.423***	0.392***
	(0.024)	(0.019)
Rain shock in first year × standardized rainfall	-0.058***	-0.013***
	(0.019)	(0.004)
Month of birth fixed effects	Yes	Yes
Year of birth fixed effects	Yes	Yes
District of birth fixed effects	Yes	Yes
R-squared	0.23	0.23
Observations	5076	5076

Notes: Absolute and squared rainfall are respectively absolute values and squares of standardized rainfall. In parentheses are standard errors clustered at the district level. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 8: Interaction between rainfall shocks prior to and after birth and mother's schooling

Variable	Daughter's Years of Schooling
Mother's years of education	0.370***
	(0.037)
Rain shock *in utero* × mother's years of education	0.029
	(0.030)
Rain shock in first year × mother's years of education	-0.054**
	(0.023)
Rain shock in second year × mother's years of education	0.052
	(0.038)
Month of birth fixed effects	Yes
Year of birth fixed effects	Yes
District of birth fixed effects	Yes
R-Squared	0.23
Observations	5079

Notes: Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25. In parentheses are standard errors clustered at the district level. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 9: Linear regression of cohort size in a district and year of birth on average rainfall shocks

Variable	Sons	Daughters
Mean rain shock in first year	-0.361	0.114
	(0.487)	(0.534)
F-statistic	23.66	18.46
R-squared	0.72	0.71
Observations	649	621

Notes: The dependent variable is the cohort size in a child's district and year of birth. Rainfall shock is a dummy variable defined as the cumulative gamma distribution of rainfall below 0.25. The mean rainfall shock is for the district and year of birth. In parentheses are standard errors. Stars indicate significance of two-tailed tests. *Significant at 10%, **significant at 5%, ***significant at 1%.