The Effects of Household Shocks on Children's Schooling in Tanzania.

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Abstract

This study examines effects of household shocks on children's schooling in Tanzania. Using data from the Tanzania National Panel Survey - 2008–2013 and the random-effects probit regression model, the study analyses the link between the shocks and child schooling, measured by school attendance and truancy. The results show that the shocks (weather, food price rises and death of a family member) affect school attendance. Furthermore, education of the head of the household increases the probability of child school attendance and reduces the probability of child truancy. Access to credit is found to increase the probability of child school attendance. Therefore, measures to help the poor and marginalized households to afford their children's education include improving their access to credit and establishing pro-poor policies, such as improving irrigation schemes and promoting drought-resistant crops, which would enhance agricultural production, increase incomes and improve vulnerability to shocks.

Keywords: household shocks, panel data, school attendance, truancy, Tanzania

1. Introduction

Household shocks lead to loss of income and assets and can plunge the affected households into poverty (Dung, 2013; Atake, 2018), thereby causing some non-poor households to fall into poverty. The children from poor families are among the most vulnerable groups to the effects of various household shocks (Zamand & Hyder, 2016). These shocks may include the following: parental job loss, parental ill health or parental death, livestock loss, weather shocks, food price rises and natural disasters, among others (Hyder et al., 2015). When these shocks occur at the early stage of childhood development, they can cause child under-nutrition, which in turn could affect the child's cognitive development and later affect their schooling (Ito & Kurosaki, 2009; Escobal et al., 2005). The evidence show that the children who suffered early life shocks tend to have low cognitive ability in school (Ferreira & Schady, 2009). In addition, they also tend to have low school attendance and poor behavioural outcomes in their adulthood (Krutikova, 2010; Walker et al., 2007).

Furthermore, household shocks can delay a child's enrolment to school and could reduce the capacity of households to afford some costs associated with child

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schooling (David et al., 2012).[1] This study has analysed the effects of household shocks on child schooling in Tanzania and examined whether access to credit mitigates the effects of household shocks, thereby improving children's schooling.

Various factors influence the extent to which the household shocks affect child schooling. These factors include the magnitude and nature of the shocks, assets that a household possess, the saving nature of a household, the ease of accessing credit as well as the characteristics of a child, a household, and the community (Ferreira & Schady, 2009; Escobal et al., 2005; Arslan et al., 2017). Evidence on the effects of household shocks and child schooling has not been consistent. Many of the empirical studies in developing countries found the negative association between household shocks and child schooling (Duryea et al., 2007; Hyder et al., 2015; Fatoke-Dato, 2015).

Poor families with limited ability to cope with household shocks through formal coping strategies normally rely on informal coping strategies to smooth consumption during the period of shocks (Kinsey et al., 1998; Dhanaraj et al., 2019). These families may choose to reduce spending on children's schooling or to withdraw their younger children from school and engage them in child labour (Skoufias et al., 2012; Ito & Kurosaki, 2009; Dillon, 2013). The potential reallocation of resources by poor households has both direct and indirect effects on child school attendance (Beegle et al., 2009; Woldehanna & Hagos, 2015). For example, when parents opt to withdraw their children from school, a child's attendance is affected, with the effects extending to future schooling (Ito & Kurosaki, 2009). In addition, these short-run mechanisms adopted by poor households have both short and long-run implications on the future welfare of children (Woldehanna & Hagos, 2015; Bandara et al., 2015).

However, evidence shows that access to credit is a good economic policy, especially for poor households, which cannot insure themselves against household shocks (Bocher et al., 2017; Hazarika & Sarangi, 2008; Flug et al., 1998). Wealthier households are able to cope easily with shocks because they can easily access credit as compared to non-wealthier households (Gertler & Gruber, 2002). Yet, empirical evidence on Tanzania with regard to the use of credit as a safety net in mitigating the effects of shocks is still limited, despite the appreciation that the effects of household shocks on child schooling would enhance the effectiveness of policies. Thus, this study has attempted to fill that gap.

Tanzania has made a considerable progress in the schooling system since the establishment of Universal Primary School for all (URT, 2007). Thus, soon after the implementation of UPE, the enrolment and primary school attendance rates increased from 66 percent in 2001 to 97.3 percent in 2007 (National Bureau of Statistics [Tanzania], 2018). Nevertheless, despite the tremendous increase in child

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[1]These costs include costs for books, school uniforms, and bus fare for the children whose schools are located far from their home (Akaguri, 2014).

school enrolment, the Tanzanian education system faces several challenges. The available education statistics in Tanzania show that as of 2016, the primary school completion rate was approximately 47.3 percent (URT, 2016). In the same year, 14.2 percent of primary school-aged children were out of school (URT, 2016). In addition, notwithstanding the low child school attendance in Tanzanian schools, truancy and dropouts from school is still a serious concern. It is reported that approximately 95.6 percent of absenteeism in primary school is accounted to truancy (URT, 2016). Perhaps the high rate of truancy and low school attendance could be emanating from the disorganized schooling system. For example, the evidence in the literature shows that the system, does not provide adequate support for children who fall behind (Escobal, et al., 2005; Ouma et al., 2017; Gaydosh, 2015). This lack of support is particularly more detrimental to children who cannot attend school because of various socio-economic factors, such as household shocks, which cause volatility in households' incomes (Escobal, et al., 2005; Ouma et al., 2017; Gaydosh, 2015).

Analysing the effects of household shocks on child schooling is particularly relevant for Tanzania, where about 75 percent of its population relies on mainly subsistence agricultural activities to earn a living (Letta et al., 2017). Approximately 26.4 percent of the population is still living below the national basic need's poverty line (National Bureau of Statistics (NBS) [Tanzania], 2018), which shows that poverty is still high in the country. Furthermore, the formal coping strategies to household shocks in Tanzania, such as crop insurance, formal credit and insurance markets and social protection for death shocks are limited or may not exist. In addition, about 27 percent of the Tanzania's households face financial exclusion (NBS [Tanzania], 2018). On the other hand, only 10 percent of the population have access to credit in the country (NBS [Tanzania], 2014). Under these circumstances, households resort to informal strategies to cope with the shocks.

2. Literature Review

2.1 Theoretical Literature Review

The most theoretical approach used in many empirical studies to analyse the determinants of child schooling is the Human Capital Model (Becker, 1964; Mincer 1974; Schultz, 1972). According to the Human Capital theory, households choose to maximize the joint utility function of all members in the household (Schultz, 1972). Utility is maximized to determine the quality and quantity of the children, consumption of leisure as well as the quality of goods from the market. Individuals always optimize their gains by evaluating the direct and indirect costs of schooling. Moreover, they compare schooling costs and the expected returns to the children resulting from schooling. The direct school cost include school fees, school supplies, clothing, as well as transport costs, whereas opportunity cost constitutes the indirect costs[2].On the other hand, the benefits of schooling outcomes are the expected higher earning capacity and the improved quality of life.

[2]The opportunity cost of schooling is the income forgone to pursue schooling at the expense of undertaking alternative activities.

The parents would choose to send their children to school if the future discounted value from additional years of schooling in the future is greater than the expected discounted value of the additional schooling costs currently (Pal, 2004). The demand for child schooling may also be influenced by supply side factors, such as the wealth of the household as well as access to school quality. Child school enrolment and attendance choices are mainly influenced by various factors, including the household's demand for schooling, government policies, household’s socio-economic factors and demographic factors, such as household shocks, which cause the volatility of the household’s income (Woldehanna et al., 2006). The study has harnessed these theories to analyse the effects of household shocks on child schooling in Tanzania.

2.2 Empirical Literature Review

A number of studies in the literature have analysed the effects of household shocks on schooling in various countries. Marchetta and Tiberti (2018) conducted a study on weather shocks and school attendance in Madagascar. The study used the panel data set of years 2004 and 2011. A bivariate probit model was employed in the main analysis. The findings indicated that negative rainfall deviations and cyclones affect negatively the lagged probability of children attending school, and encourage both men and women to engage in work. The children affected most by the rainfall shocks were those from poor families, which did not have access to insurance and credit.

Glick and Walker (2016) analysed the effects of households’ shocks on education investment in Madagascar. The study used household and school level survey conducted in the period 2004–2005 in 73 districts in Madagascar. The discrete hazard model was employed to capture enrolment and dropout decisions. Then the study estimated the model by using the maximum likelihood estimation. The study found that the probability of a child dropping out of school increases significantly when a household experiences illness, death or asset loss.

Dhanaraj (2016) examined the effects of parental health shocks on children’s schooling in India. The study employed the longitudinal data from the Young Lives project, which is conducted in the Southern state of India. Dhanaraj (2016) used both the younger and older cohorts of children and found that the health shocks among poor families decrease the human capital investment in the children, thereby decreasing their earnings in the future. The study further found that parental health shocks caused a temporary delay in children’s school enrolment of the younger cohort and reduced the school attainment of older children by 0.26 years.

Hyder and Kohler (2015) investigated the effects of negative economic shocks on child schooling in rural Malawi. The study employed longitudinal data from Malawi Longitudinal Study of Families and Health surveys (MLSFH) for six survey waves (1998, 2001, 2004, 2006, 2008 and 2010). It analysed the panel of the children aged 6 and 15 years in 2008, based on the information from female and male respondents for the years 2006 and 2008, respectively. They used the logit model and the 2SLS to estimate child school enrolment outcome and child school attainment gap, respectively. The study found that the community level shocks have a strong, negative effect on the children's school enrolment. These effects seemed to be higher when men reported the shocks, in contrast to women.

Alam (2015) studied the impacts of parental health shocks on child labour and educational outcomes in Tanzania, using longitudinal data from the Kagera Health and Development Survey (KHDS) conducted in Kagera Region, Tanzania for a period 1991–1994. The study found that the illness of the father reduced the school attendance of the children and it had long run impacts on child school completion. In addition, the study found no effects of the illness of the mother on child schooling.

Krutikova (2010) studied the long-run effects of income shocks on schooling in Tanzania using a thirteen-year panel survey of households in rural Tanzania in examining the effects of income shocks (proxied by rainfall shocks) on education attainment of the children (aged seven to 15 years) within the rural households in their adulthood. The findings showed that crop shocks (pests, theft, and fire) affects children schooling of the older age cohort as compared to adults.

Using the KHDS of Tanzania, Ainsworth et al. (2005) analysed the effects of adult mortality (death of the parents) on children's schooling. The study employed the maximum likelihood probit regression model to examine the link between parental death and child schooling. The findings of their study showed that a child's school attendance tend to delay for an orphan who lose a father. Their study also indicated that girls were more likely to reduce school hours after parental loss.

2.2 Synthesis of the Review

This study contributes to the literature in three ways: First many empirical studies on similar topics are for rural settings, for example, Alam, 2015; Krutikova, 2010; Hyder et al., 2015. However, shocks affects both urban and rural households. Thus, this study has incorporated both the rural and urban areas in the analysis. Secondly, many of the previous studies on the effects of household shocks on child schooling in Tanzania did not include access to credit, which mitigates against shocks, with the exception of Bandara et al. (2015). However, with regard to access to credit, Bandara et al. (2015) sought address its link to shocks and child labour. In addition, they used data from only the second wave of the NPS. Thirdly, previous empirical studies on Tanzania analyse specific regions, for example, Alam, 2015 and Krutikova, 2010. In addition to being regional studies, the studies used data sets from the Kagera Health and Development Survey (KHDS), covering years 1991–1994 and 2004, whose data may be out-dated. Additionally, the data set for one region may not represent correctly the situation for the whole country. In this regard, this study has used a more comprehensive and richer dataset from the Tanzanian National Panel survey (2008–2013) to fill the existing gap in literature.

3. Methodology

3.1 Theoretical Model

This study adopted the demand for school framework by Becker and Lewis (1973), as applied by Khandker et al. (1994). The households are assumed to care about their future revenue and their children's wealth. The future revenue of the children is factored in their parents' utility function. Thus, the parental utility function is presented by:

$$U = f(S, L\ C) \qquad (1)$$

Where; S represents child schooling, L, shows the children's leisure and C shows household consumption.

The child schooling is dependent on the home-based produced goods, which depend both the home produced-inputs and the market-purchased inputs. Thus, the child schooling production function is represented as:

$$S = S(M, K, \mu) \qquad (2)$$

Where M represents a vector of market purchased inputs. These inputs include papers, books, exercise books, and pencils, among other school inputs; K represents time devoted to child schooling and μ represents both individual and child schooling endowments.

The child is also constrained with time. Thus, the total time which is available for a child (H) can be spent in income generation from child labour, leisure, and child schooling denoted by Y, L, and N, respectively, for child labour hours, leisure, and child schooling inputs, which is represented by the following equation:

$$H = f(Y, L, N) \qquad (3)$$

On the other hand, the parents face income/budget and credit constraints. This is especially so when the financial markets are not complete. According to Jacoby and Skoufias (1997), when households have access to the credit, they may be able to borrow to offset transitory household shocks, thereby leaving the decision of children's school attendance unaffected. In addition, credit access also enables poor households to reduce the effects of permanent household shocks, such as parental death shocks, on current consumption, which includes a child's school resources. The household income constraints or the budget-constraint is represented by the following equation:

$$P_M M + P_N N = \theta W + \tau \qquad (4)$$

Where P_M and P_N represent the relative prices of the home-produced inputs and child schooling inputs, respectively. W represents parental income, θ shows the household shocks (rise in food prices, weather, death and severe water shortage) that affect the welfare of the household and τ represent credit access by members of the household.

The optimal amount of the input purchased, for the production of child schooling, and the optimal amount of time spent on child schooling and on leisure can be obtained by maximizing the utility function given by Equation 1, subject to the constraints that are given by Equations 3 and 4. The optimization process results in the reduced demand function for child schooling, which is represented by Equation 5.

$$S = D(P_M, P_{N,} W, \theta, \mu, \tau, F_\alpha, J_\alpha) \qquad (5)$$

The independent variables in the reduced form equation are the relative prices, the income of the households W, the household shocks (θ), access to credit (τ), school and individual endowments (μ), and the parental shocks, denoted by $F_\alpha$and J_α, respectively. Nevertheless, the structure of the dataset could not allow for the use of all independent variables as presented in Equation 5. Hence, we included only individual endowments and characteristics such as age, sex, education of the parents, marital status, and community characteristics, such as location/residence.

3.2 Data

This study uses the national panel survey of Tanzania, 3 waves. It is part of Living Standard Measurements Survey (LSM) conducted by the National Bureau of Statistics of Tanzania in collaboration with the World Bank. Though currently there is the fourth and fifth waves in Tanzania, this study did not use them. The reason for not using them is that the fourth and fifth waves drew their sample from a different Master Sample Plan, hence it was difficult to obtain common household identification in all waves. Wave 1 of the NPS ran from October 2008 to September 2009; wave 2 took place from October 2010 to September 2011 and wave 3 took place from October 2012 to September 2013. Wave 1 comprises 3,265 households with about 16,708 observations; Wave 2 comprises of 3,924 households with 20,559 observations; and Wave 3 comprises 5,015 households with about 25,412 observations. The households that were re-interviewed in the second round were 3,168. In all the three waves, 3,088 households were re-interviewed, with the attrition rate being 5.4 percent in all the five years. This rate is relatively low when compared to the attrition rates in the panel surveys from other developing countries, which other studies have used (Outes-Leon & Dercon, 2008). The NPS comprises the household, community and agricultural questionnaires. The survey compiles data on the education of the children above five years of age, including their attendance, if the children were enrolled in a school, the highest grade completed in each round of the survey, and information on their school achievements, among others. Apart from the information on education, the Household questionnaire collects data on the characteristics of households, community and child, such as age, gender, and location.

To obtain the sample for the study, we followed all individuals included in all the three waves (2008–2013) whose age ranged from seven to 13 years during the survey period. These individuals are known as children in this study. They are children attending primary school in Tanzania (URT, 2014). The study focused on children aged 7–13 years because in Tanzania, the minimum age for starting primary school is seven years. For a child who start on time, she/he may complete primary school aged 13 (URT, 2007). However, applying the age restriction could result in sample selection bias. However, according to Winship and Mare (1992), the use of panel data enables a researcher to control for unobserved and observed variables, which provide a room to alleviate the selection bias. However, if the selection is only on the observed dependent variable, then selection bias is not a problem (Winship & Mare, 1992).

After restricting the age of an individual to a range of 7–13 years, we remained with 2,956 out of 16,708 in Wave 1; 3,559 observations out of 20,559 in Wave 2; and 4,283 observations out of 25,412 in Wave 3. The appending process made the observations to be 10,798 in all 3 waves. By following each cross-section unit in all the three waves, the study remained with a balanced panel data with 6,813 observations, which was the basis of the main analysis.

3.3 The Outcome Variables

The outcome variables for the study are *child school attendance* and *child truancy*. From the household, the questionnaire explores the question which reads "*Is your child currently attending school*" The response to this question was "*Yes*" or "*No* " Therefore, the child school attendance is measured as a dummy variable indicating 1 if a child is currently attending school and 0 if otherwise. The survey shows that about 83 percent of the primary school-aged children were attending school in all three waves, whereas about 85 percent, 86 percent and 79 percent were attending school in the survey year 2008/09, 2010/11, and 2012/13, respectively. Child school attendance and truancy are all measured for the time of the interview.

The second outcome variable is *child truancy*. In the questionnaire, another question is asked, "*Has (NAME) missed school in the last two schooling weeks?* "The response to this question was "*Yes*" or "*No*". The next question was, "*Why was (NAME) absent from school?",* whereby various reasons for missing school were recorded. These reasons include the following: public holiday, the school has been closed (not in the break), the school closed (in a break), absent teacher, illness (child), illness (household member), funeral, disciplinary action, cannot meet costs, the child refused, and child had to work, among others. The questions were used to construct the child "truancy" variable. From the mentioned reasons, we selected the reasons that kept the children out of school other than permission, public holiday, and school closure. The reason for this selection is that a child is obliged to attend school for all school days, except when permission is granted or when it is a holiday (Rodriguez & Conchas, 2009). The variable is defined as a dummy variable, which indicates 1 if a child missed school without a valid reason (due to absent teacher, illness child, illness of the household member, funeral, cannot meet cost, the child refused, and child had to work in the past two schooling weeks) and 0 if otherwise. We used these categories to generate a truancy variable because according to the literature, the commonly accepted definition of truancy is absenteeism from school without permission (Rodriguez & Conchas, 2009).

3.4 Independent Variables

The current study used household shocks as the main independent variable, which constituted four most significant shocks reported by the households to affect their incomes and welfare or cause loss of assets. The shock is measured as a vector of dummy variables, which indicates 1 if a household experienced at least one of those four events in the past two years prior the survey and 0 if otherwise.

3.4.1 Household Shocks

A shock is defined as unanticipated or any adverse event that causes income loss for households, reduces the consumption of a household, and causes the loss of assets of households (Dercon et al., 2005). In this study, household shocks have been defined similarly as in Dercon et al., 2005. The Household Questionnaire of the National Panel Survey has a section headed, "*Recent Shocks to Household Welfare*". The section focuses on the household shocks faced by the households in the five years preceding the interview date. It starts with this question "*Over the past five years, was your household severely affected negatively by the following events/shocks?"* Then the adverse events were listed and the household's head had to respond by answering "*YES*" if the household had been affected by any of the events among those listed, or "*NO*" if it had not experienced any adverse effect from the events. The next question was, *"When did this shock occur?*". With regard to this question, the survey keeps record of the year and month of the shock occurrence, which enabled us to generate the shock-variable falling within the two years prior to the survey date. The reason for choosing two years was to focus on the recent shocks. Thus, the analysed shocks were limited to only those that occurred between the two waves.

Other issues from the questionnaire were the following *"Rank the three most significant/severe shocks/adverse events you experience*d", "followed by, "*Did it (Shock) cause a reduction in household income and/or assets*? Thus, the questionnaire recorded the most significant adverse events/shocks. From these two records, the study chose the first four significant shocks /events that households experienced (weather shocks, death, food price rises, and severe water shortage) that caused a reduction in the income of the household and or asset loss. Weather could be very damaging in Tanzania, since almost 75 percent of the population rely on agricultural activities (Chongela, 2015). Because agricultural activities contribute significantly to livelihood, droughts, floods, pests, and diseases also cause significant food losses, which, consequently, result in volatilities in food prices. In this regard, the most affected crop is maize, which is the staple food in most parts of Tanzania (Huka et al., 2014). On the other hand, almost 70 percent of the households that live in semi-arid areas, such as Dodoma, experience severe water shortages (Mkonda, 2015). In Tanzania, social assistance programs are limited; and in some places, they do not exist. Thus, in the absence of such assistance, poor households may experience death shocks (Gaydosh, 2015).

This study employed other control variables, in addition to those already discussed. These included household size, consumption, and real expenditure. Included also are the occupation of the head of the households, socio-economic status of the household head, for example, age of the head, sex, marital status, and level of education; access to credit, child's age, and child sex.

3.5 Empirical Model

The panel random effect probit model is used in this study because it is advantageous over other models in that the dependent variable of the model is dichotomous. This dichotomous characteristic enables the model to analyse dependent variable outcomes with individual heterogeneity in the panel data setting, unlike other models, such as the fixed effects probit model and Linear Probability Model (Bland & Cook, 2019, Aldrich et al., 1984). Secondly, the panel random effects probit model is the most appropriate when there is no omitted variable bias in the dataset (Williams, 2018; Torres-Reyna, 2007). To choose between the panel random effects probit model and the fixed effects probit model, the study used the Regression Specification Error Test (RESET) (Shukur & Mantalos, 2004), which seeks to gauge whether or not the model suffers from omitted variable bias. The *p-value* result was smaller than the 0.05 threshold of the RESET test; which means that the null hypothesis could not be rejected. These results (presented in Table 1 in the Appendix) indicate that the model is correctly specified. This confirmation that there is no omitted variable bias in the model cleared for the use of the random effect probit regression model. Other statistical tests conducted include the multicolinearity, heteroscedasticity and endogeneity tests.

Thus, the econometric model is specified as follows:

$$y_{ijt} = \beta_0 + \beta_1 Shock_{jt} + \beta_2 X_{it} + e_{it} \qquad (6)$$

Where y represents the school attendance and child truancy of child i living in household j in time t (t = (2008/09, 2010/11, and 2012/13). $Shock$ measures the household shocks, X_{it} represent child or household characteristic i in time t, β_i are the parameters to be estimated and e_{it} is the stochastic term.

1. Findings and Discussion

The descriptive statistics for the study are summarized in Table 1. The weather shocks include all droughts and floods that occurred in the two years before the survey was undertaken. Death shocks include death of either a household member or a parent. In Tanzania, the mortality rate is high, due largely to prevalence of malaria and HIV/AIDs (Ainsworth et al., 2005). Shock of a rise in food prices captures the highest rise in the price of food, mainly the staple food, such as maize.

As Table 1 shows, 19 percent of the households in the sample experienced a rise in food prices in all waves; death shocks affected 16 percent of the households in all waves; and weather shocks and severe water shortage shocks affected 7 percent of the households.

Table 1: Descriptive Statistics

Variable	All Waves (2008/09, 2010/11 & 2012/13)					2008	2010	2012
	N	***Mean***	***Std. Dev.***	***Min***	***Max***	***Mean***	***Mean***	***Mean***
Child school attendance (Yes=1)	6813	0.834	0.372	0	1	0.85	0.86	0.79
Child Truancy	5682	0.017	0.130	0	1	0.018	0.020	0.012
Household size	6813	4.996	3.055	1	55	4.89	5.14	4.96
Child age(years)	6813	9.961	1.967	7	13	9.97	9.95	9.97
School start age	6813	6.992	1.156	5	13	7.02	7.06	6.9
Marital status(Married=1)	6813	0.800	0.400	0	1	0.780	0.800	0.790
Credit access (Yes =1)	6813	0.102	0.303	0	1	0.07	0.12	0.12
Child sex (male=1)	6813	0.486	0.5	0	1	0.49	0.49	0.48
Household head sex (male=1)	6813	0.782	0.413	0	1	0.79	0.78	0.78
Agricultural employment	6813	0.247	0.431	0	1	0.246	0.244	0.25
Salary employment	6813	0.023	0.151	0	1	0.018	0.026	0.026
Business employment	6813	0.05	0.217	0	1	0.052	0.053	0.044
Self-employment	6813	0.165	0.371	0	1	0.166	0.156	0.172
No jobs	6813	0.515	0.5	0	1	0.518	0.52	0.508
Residence (Rural=1)	6813	0.756	0.475	0	1	0.746	0.754	0.754
Weather shocks	6813	0.073	0.261	0	1	0.07	0.08	0.07
Food price rise shocks	6813	0.188	0.391	0	1	0.19	0.19	0.19
Severe water shortage shocks	6813	0.069	0.253	0	1	0.07	0.07	0.07
Death shocks	6813	0.155	0.362	0	1	0.14	0.17	0.16
Education real exp(log)	6813	11.583	1.173	9.211	16.016	11.32	11.6	11.83
Consumption expend. (log)	6813	14.683	0.778	11.7	17.38	14.49	14.66	14.9
primary education	6813	0.706	0.483	0	1	0.685	0.675	0.761
secondary education	6813	0.223	0.328	0	1	0.230	0.238	0.170
tertiary education	6813	0.071	0.432	0	1	0.085	0.087	0.069
Number of observations						2271	2271	2271

Source: Author's computation from three waves of TNPS.

The mean for child age is 10 years for all waves taken together and for individual waves, which implies that a majority of children were in Standard 4 during the time of the survey. Male children constitute an average of 49 percent of the sample, whereas female children constitute about 51 percent of the sample; thus, the distribution between male and female children in the sample is equal. In addition, on average, the marital status for 80 percent of the households is "married". The average household size is on average five people for the combined three waves and for individual waves separately; that is, it is similar to the national average, which ranges from 4.6 to 5 (National Bureau of Statistics [Tanzania], 2014). Moreover, on average 71 percent of household members had attained primary education, 17 percent secondary education and 7 percent tertiary education.

The descriptive statistics further show that for all the three waves, about 78 percent of the households are male-headed, which implies that many of the societies in Tanzania are patrilineal. The percentage of households benefiting from access to credit in all three waves was 10 percent. Furthermore, about 75 percent of the households in the sample were rural dwellers. The education expenditure (as calculated from the antilog of 14.68) was on average TZS 238,501 per annum, which is approximately USD 103.6. The minimum school-start age in the sample is seven years. This age is similar to that of Ethiopia, while it differs with that of Kenya, which is 6 years and that of Uganda, which is 5 years. Moreover, child truancy in the sample accounted for an average of 2 percent over all the three waves.

4.1 *The Effects of Household Shocks on Child School Attendance*

The study carried out regressions with regard to the effects of household shocks on child school attendance in two stages. In the first stage, the study included all the shocks in one regression equation to estimate simultaneously the effect of each shock on child school attendance. In the second stage, the study analysed the shocks using separate regression equation for each particular shock. Thus, Table 2 reports the estimates of Marginal effects of the first-stage regression of the shocks, whereas Table 3 reports the results of the second stage, based on separate regressions for each of the shocks on child school attendance.

Table 2: Random Effects Probit model with respect to all the Household Shocks on Child School Attendance

Variables	School Attendance [1]	School Attendance [2]
Weather shocks		-0.190
		(0.134)
Food price rise shocks		-0.099
		(0.084)
Severe water shortage		-0.099
		(0.135)
Death shocks		-0.181**
		(0.088)
Child age(Months)	0.170***	0.171***
	(0.017)	(0.017)
Child sex(Male=1)	-0.249***	-0.249***
	(0.066)	(0.066)
Credit Access(Yes=1)	0.129	0.122***
	(0.107)	(0.107)
Household size	-0.014	-0.014
	(0.012)	(0.012)
Marital status(married=1)	0.099	0.099
	(0.085)	(0.085)
Household head sex(male =1)	-0.193*	-0.194*
	(0.099)	(0.099)
Secondary education	0.471***	0.465***
	(0.136)	(0.136)
Tertiary education	0.380***	0.375***
	(0.123)	(0.123)
Consumption real exp(log)	-0.029	-0.033
	(0.055)	(0.055)
Residence(Rural=1)	-0.205**	-0.197**
	(0.084)	(0.084)
Constant	0.547	0.544
	(0.802)	(0.802)
Observations	6,813	6,813
Number of UPI3	2,271	2,271

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

As Table 2 reports, the death shock was negatively and statistically significant at 5 percent, other factors remaining constant. This result means that a death shock is associated with a lower probability of child school attendance. Specifically, the study found that when the household member dies, the probability of a child attending school decreases by 18 percent, which is similar to findings of some previous studies (Dhanaraj, 2016; Pörtner, 2016; Gertler, et al., 2003). The remaining shocks were not statistically significant; perhaps, due to entering simultaneously into one regression equation.

The results with respect to marginal effect from the regression equations for each shock on child school attendance are presented in Table 3. Examining each shock separately enabled us to understand how each individual shock correlates with the outcomes, which are child school attendance (Table 3) and child truancy (Table 4). The estimates conducted in Table (3) and Table (4) provides slightly varying findings for the control variables since only a single explanatory variable is the one that change in each estimation. Therefore, in the four estimations conducted, values of the control variables have slight variation.

The findings further show that the effect of weather shocks on child school attendance was negatively and statistically significant at a 1 percent level, as shown in column 1 of Table 3. This result implies that weather shocks are associated with a lower probability of child school attendance, such that when the household experiences weather shocks, the probability of a child to attend school decreases by 18 percent. This finding share commonality with some previous studies that found a negative association between weather shocks and child school attendance (Adejuwon, 2016: Marchetta et al., 2018; Millett & Shah, 2012; Agamile & Lawson, 2018). Weather shocks decrease child school attendance through two channels. Droughts shocks lead to food loss, which result in under-nutrition for younger children, thereby affecting negatively the children's health, especially those from poor households (Dung, 2013). The children's poor health may affect the ability of a child to attend school, since poor health is associated with children's morbidity. Shah & Steinberg (2012) showed that children who experience drought in utero were associated with a 2.6 percent lower likelihood of recognizing the numbers in school. Secondly, when mothers face floods, especially during pregnancy, the cognitive development of the foetus is likely to be affected, especially due to contamination of water, which would cause various water-borne diseases. This situation might force some parents to programme child schooling to match with a child's lower cognitive ability (Ugaz & Zanolini, 2011).

The effect of shocks due to a rise in food prices on child school attendance was found to be negative and statistically significant at a 5 percent level, as shown in Column 2 of Table 3. The estimate show that shocks due to increase in food prices are associated with a lower probability of child school attendance. Specifically, when the household experiences a rise in food prices, the probability of a child attending school decreases by 9 percent. This result implies that an increase in the prices of food affects food security, particularly for households with low incomes.

Table 3: Marginal Effects Estimates of Household Shocks on Child School Attendance

Variables	School Attendance [1]	School Attendance [2]	School Attendance [3]	School Attendance [4]
Weather shocks	-0.184***			
	(0.133)			
Food price rise shocks		-0.092**		
		(0.083)		
Severe water shortage shocks			-0.102	
			(0.135)	
Death shocks				-0.182**
				(0.088)
Child Age(years)	0.170***	0.170***	0.170***	0.170***
	(0.017)	(0.017)	(0.017)	(0.017)
Child sex(Male=1)	-0.240***	-0.249***	-0.249***	-0.247***
	(0.066)	(0.066)	(0.066)	(0.066)
Credit Access(Yes=1)	0.138	0.136***	0.132	0.130
	(0.107)	(0.107)	(0.107)	(0.107)
Household size	-0.0186*	-0.0177*	-0.018*	-0.018*
	(0.011)	(0.010)	(0.011)	(0.010)
Marital status(Married =1)	0.099	0.098	0.098	0.097
	(0.086)	(0.086)	(0.085)	(0.086)
Household head sex(Male =1)	-0.189**	-0.187**	-0.188**	-0.190**
	(0.099)	(0.099)	(0.099)	(0.099)
Household head secondary ed.	0.456***	0.462***	0.457***	0.460***
	(0.136)	(0.136)	(0.136)	(0.136)
Household head Tertiary ed.	0.371***	0.374***	0.370***	0.373***
	(0.123)	(0.123)	(0.123)	(0.123)
Residence (Rural=1)	-0.183	-0.183	-0.183	-0.183
	(0.082)	(0.082)	(0.082)	(0.082)
Education real exp (log)	-0.007	-0.007	-0.007	-0.009
Occupation	(0.073)	(0.074)	(0.073)	(0.074)
Salary employment	0.144**	0.147**	0.145**	0.145**
	(0.217)	(0.217)	(0.217)	(0.217)
Business employment	-0.160	0.161***	-0.161	-0.160
	(0.156)	(0.156)	(0.156)	(0.156)
Self-employment	-0.050	-0.055	-0.052	-0.055
	(0.104)	(0.104)	(0.104)	(0.104)
No jobs	0.075	0.0723	0.073	0.069
	(0.087)	(0.081)	(0.082)	(0.081)
Constant	0.140	0.172	0.159	0.202
	(0.468)	(0.468)	(0.467)	(0.468)
Observations	6,813	6,813	6,813	6,813

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Households with low incomes tend to spend a high proportion of their incomes on foodstuffs. For net buyers of food, the food-prices shocks decrease the households' real incomes, thereby decreasing the households' purchasing power (Mbegalo, 2016;

Chegere et al., 2018; Dubihlela & Sekhampu, 2014). The decreased purchasing power could cause the parents to reduce expenditure on children's schooling, which would affect the school attendance. These findings are consistent with Raihan (2009), who found that a shock due to a rise in food prices tend to reduce child school attendance.

Further, findings in Table 3 show that a death shock was negatively and statistically significant at 5 percent level, which implies that death of a family member is associated with a lower probability of a child's school attendance. Thus, the estimates reveal that when a household experiences a death shock, the probability of child school attendance decreases by 18 percent (Table 3 – Column 4). The implications of the result with regard to death shocks are three-fold: One, the death of a mother affects more the girls' school attendance, since girls have to stay at home and take care of their young siblings (Pörtner, 2016). Two, death of both parents tend to reduce the household's income, thereby affecting negatively the involvement of other elders remaining in the household in the schooling of children (Dhanaraj, 2016). Three, due to income loss, spending on education could decrease, which would lower school attendance of younger children. This result is consistent with the evidence from several previous studies (Dhanaraj, 2016; Beegle et al., 2006; Pörtner, 2016; Gertler, et al., 2003).

The findings further indicated that access to credit was positively and statistically significant with a higher probability of a child to attend school. Particularly, when a household has access to credit, the probability of school attendance by a child increases by 14 percent and 12 percent, as shown in column 2 of Table 3 and column 2 of Table 2, respectively. The accessing of credit by a household implies that the household is enabled to deal with liquidity constraints, whereby it is availed the resources to purchase school requirements, such as books, pens, and school uniforms. In Nepal, Zimbabwe, and Peru, the study by Ersado (2003), revealed that when parents have access to credit, school enrolment and attendance improve.

4.2 *The Effects of Household Shocks on Child Truancy*

The Random effects probit regression results of the marginal effects of household shocks on child schooling, measured by child truancy, are reported in Table 4. Each of columns 1, 2, 3 and 4 show results of a different kind shocks, namely, effect of weather shocks, shocks due to rise in food prices, shocks due to severe water shortage and death shocks, respectively. The results revealed that the effect of experiencing weather shocks on child truancy was positively and statistically significant at a 5 percent level, which implies that weather shocks are associated with a higher probability of a child being truant. The study found that when a household experiences weather shocks, the probability of a child being truant increases by 22 percent (Table 4 - Column 1). Weather shocks, such as floods, may exacerbate child truancy because floods cause destruction of infrastructure and dwellings, which lead to loss of property and disruptions in the flows of households' incomes (Conteh, 2015).

Table 4: The Estimates of Marginal effects of Household Shocks on Child Truancy

Variables	Truancy [1]	Truancy [2]	Truancy [3]	Truancy [4]
Weather shocks	0.221**			
	(0.490)			
Food price rise shocks		-0.090**		
		(0.442)		
Severe water shortage shocks			-0.054	
			(0.505)	
Death shocks				-0.244
				(0.379)
Child Age(years)	0.015	0.021	0.014	0.014
	(0.066)	(0.067)	(0.066)	(0.065)
Child sex(Male=1)	-0.080	-0.092	-0.081	-0.069
	(0.257)	(0.263)	(0.258)	(0.253)
Credit Access(Yes =1)	-0.212	-0.236	-0.258	-0.204
	(0.435)	(0.445)	(0.437)	(0.429)
Household size	0.037	0.041	0.039	0.036
	(0.039)	(0.040)	(0.039)	(0.038)
Marital status(Married =1)	0.314	0.328	0.346	0.293
	(0.349)	(0.358)	(0.380)	(0.394)
Household head sex(Male =1)	0.127	0.127	0.126	0.139
	(0.401)	(0.413)	(0.433)	(0.395)
Secondary education	0.298	0.356	0.309	0.295
	(0.721)	(0.744)	(0.776)	(0.714)
Tertiary education	-0.198***	-0.317***	-0.221***	-0.186***
	(0.689)	(0.712)	(0.696)	(0.682)
Residence(Rural=1)	0.540***	0.554***	0.533	0.535***
	(0.327)	(0.335)	(0.327)	(0.325)
Education real exp (log)	0.205	0.206	0.203	0.204
	(0.125)	(0.128)	(0.125)	(0.124)
Business employment	-0.241***	-0.271***	-0.261***	-0.241***
	(0.064)	(0.276)	(0.007)	(0.656)
Salary employment	-0.733**	-0.734**	-0.731**	-0.732**
	(0.621)	(0.666)	(0.629)	(0.598)
No jobs	0.772	0.737**	0.732***	0.734***
	(0.198)	(0.237)	(0.204)	(0.169)
Constant	-0.007***	-0.042***	-0.067***	-0.044***
	(0.854)	(0.898)	(0.846)	(0.766)
Observations	5,682	5,682	5,682	5,682

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

In addition, floods might instigate a rise in infections, such as water-borne diseases, which would cause children to stay at home because of illnesses, thereby increasing the probability of truancy (Mudavanhu, 2014). Similarly, whether shocks, such as heavy rains, could keep children away from school, whereby some parents could choose to use their labour for agricultural activities during the rainy season. The study found shocks due severe water shortages to be statistically insignificant, perhaps because during the period of the survey, many of the children in the sample were residing in areas that did not experience severe water shortages.

The experience of shocks due rise in food prices on child truancy was negatively and statistically significant at a 5 percent level, keeping other factors constant (Table 4 - Column 2) This result shows that shocks due to a rise in food prices are associated with a lower probability of a child being truant. Particularly, when a household experiences shocks due to rise in food prices, the probability of child truancy decreases by 9 percent. The intuition behind this result is that when food prices rise, it is more likely that a household will get more income from the sale of food items, being the supplier of the commodity, which would tend to lead to decreased child truancy (Brüntrup, 2008). Child truancy would decrease because the increase in the households' incomes will first enable households to afford more food, thereby leading to improved children's health. When the children are in good health and not hungry, they are less likely to be truant, since truancy is often driven by the need to search for food. In addition, the increase in households' incomes will enable the parents to bear other schooling costs, which would reduce the rate of truancy.

4.3 The Marginal Effects of Household Shocks on the Control Variables

The estimates of marginal effects of household shocks on control variables are also presented in Table 3 (with respect to school attendance) and Table 4 (with respect to child truancy). Child age is positively and significantly associated with child school attendance at a 1 percent level (Columns 1–4 of Table 3). The estimate in this regard is that a one-year increase in the child's age increases the probability of a child's school attendance by 17 percent in column (1–4, Table 3). However, it was not significant in explaining the probability of a child being truant, as shown in Table 4. On the other hand, being a male child was negatively and significantly associated with child school attendance (Table 3). Specifically, when a child is male, the probability of school attendance decreases by 24 percent (Table 3 column 1–4). However, this variable has no significant effects on a child truancy, as shown in Table 4. Furthermore, the findings, as shown in Table 3, indicate that, keeping other factors constant, the household size was negatively and statistically significant on the child school attendance, but it does not affect child truancy, as shown in Table 4.

The education level of the head of the household shows varying results. Findings show that when the head of the household has attained tertiary education, the probability of a child being truant from school declines by about 19 percent, 31, 22 and 18 percent, as shown in Columns 1-4, respectively (Table 4). In addition, residence was positively and statistically significant at a 1 percent level of significance in three columns 1, 2, and 4 (Table 4). This result indicates that residence was associated with a higher probability of a child being truant. Particularly, when the households are in the rural areas, the probability of their children being truant increases by 54, 55 and 53 percent, as shown in Columns 1, 2 and 4 of Table 4, respectively, which are higher in comparison with those who reside in urban areas. We may conjecture that a higher probability of child school truancy in rural areas is attributed to walking for long distances from home to school. However, this study did not test this claim.

The findings in Table 3 further revealed that, that business employment was positively and statistically significant at 1 percent level in Column 2 (Table 3). However, it is negatively and statistically significant at 1 percent level in columns 1–4) in Table 4. These results shows that being engaged in business occupation by the head of the household is associated with a higher probability of child school attendance. Particularly, when the household engaged in business, the probability of a child to attend school increases by 16 percent (Table 3 – Column 2). This implies that households that engage in businesses are likely to get income to support their children's education. On the other hand, salaried employment was positively and statistically significant at 5 percent level (Table 3 – Column 1-4), while it is negatively and statistically significant at 5 percent level in columns 1–4) of Table 4. This shows that the children residing in households with salaried employment are more likely to attend school and less likely to be truant, since their parents are more likely to have enough income to support for their schooling. Furthermore, the no jobs occupation was also positively and statistically significant at 5 percent level ((Table 4 – Column 2), and also positively and statistically significant at 1 percent level(Table 4 –Column 3 and 4). Particularly when the household has no job, the probability of child truancy increased by 73 percent, as shown in columns 2, 3 and 4 of Table 4. These findings imply that the children from the households with no jobs are more likely to be truant, as their parents might not have enough income to support their schooling.

4. Conclusion and Policy Implications

This study examined the effects of household shocks on child schooling in Tanzania. Specifically, it examines the probability of child school attendance and child being truant due to the effects of shocks using data from three waves of the National panel survey covering the period 2008–2013. These data were used to obtain estimates of the random effects probit model, with a view to evidence the link between household shocks and child schooling.

To this end, the findings of this study indicated that weather shocks, food price rise shocks and death of family member decreases the probability of child school attendance, whereas weather shocks increase the probability of a child being truant. These findings imply that, in Tanzania the school-aged children still miss school due to household shocks. In addition, the findings indicated that households with access to credit are more likely to send their children to school. The reason behind this finding is that households that have access to credit can manage to deal with credit constraints. In this regard, policies geared at enhancing credit access credit should extend credit more efficiently and affordably, even to the poor. In addition, information on borrowers should be accurate and reliable so that they can access credit conveniently. The affordable credit empowers households to manage profitably their economic activities. This will help the households to generate more incomes and afford foodstuffs, instead of withdrawing their children from school during the period of shocks to smoothen consumption.

Furthermore, the findings suggest the need for the Tanzanian government to develop policies that are pro-poor, such as providing fertilizers, improving irrigation schemes, and introducing drought-resistant crops (such as cassava, sorghum and sweet potatoes), especially when there is drought. This will help the poor households to improve on their agricultural production and earn more incomes to cater for family needs, especially to finance the education of their children, even when there is household shocks.

The study also showed a positive association between the education of the head of the household and child school attendance in favour of higher education. Thus, to alleviate low school attendance and improve schooling, policy should include opportunities for heads of the household with low education to improve on their levels of education.

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Appendix

Table 1: Omitted Variable Bias Test

Ho: Model is **Specified**	Ha: Model is **Mis-specified**
* Ramsey Specification ResetF Test	
- Ramsey RESETF1 Test: Y= X Yh2	= 6.315 P-Value >F (1, 2281) 0.0120
- Ramsey RESETF2 Test: Y= X Yh2 Yh3	= 3.300 P-Value >F (2, 2280) 0.0371
- Ramsey RESETF3 Test: Y= X Yh2 Yh3 Yh4	= 2.210 P-Value >F (3, 2279) 0.0849
* DeBenedictis-Giles Specification ResetL Test	
- Debenedictis-Giles ResetL1 Test	= 0.294 P-Value > F(2, 2280)0.7449
- Debenedictis-Giles ResetL2 Test	= 0.343 P-Value >F (4, 2278)0.8490
- Debenedictis-Giles ResetL3 Test	= 0.798 P-Value >F (6, 2276)0.5710
* DeBenedictis-Giles Specification ResetS Test	
- Debenedictis-Giles ResetS1 Test	= 0.591 P-Value > F(2, 2280)0.5537
- Debenedictis-Giles ResetS2 Test	= 0.575 P-Value >F (4, 2278)0.6808
- Debenedictis-Giles ResetS3 Test	= 0.673 P-Value >F (6, 2276)0.6714
- White Functional Form Test: E2= X X2	= 23.240 P-Value >Chi2 (1) 0.0000

*** Regression Specification Error Tests (RESET) - Model= (xtre)