GOOD OR BAD TIMING? THE EFFECTS OF PRODUCTIVITY SHOCKS ON EDUCATION AND ON SCHOOLING PERFORMANCE

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Good or bad timing? The effects of productivity shocks on education and on schooling performance.*

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Abstract

It is often argued that negative productivity shocks have adverse effects on education in developing countries. In this paper, I assert that positive productivity shocks can also come at the expense of education. I present a theoretical model to predict the mechanisms when shocks occur in early childhood and in school-age. To capture exogenous shocks in productivity, I exploit variation in intensity of climate and prices across location and over time. The empirical part provides evidence that in early childhood, positive productivity shocks have persistent positive consequences on schooling performance. In contrast, the relationship becomes counter-cyclical when children are of school age. Current positive shocks increase child labor, reduce schooling performance, and decreases the education attainment when shocks become recurrent.

Keywords: Human capital investment, cognitive skills, weather shocks, price shocks, Tanzania.

JEL Codes: I25; D15; 015.

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1 Introduction

The United Nations Environment Programme (UNEP) records that natural disasters such as droughts and floods have been multiplied by two over the last 25 years. Concurrently, the Food Agriculture Organization (FAO) highlights that commodity prices have become more volatile. This increasing number of shocks, which sparks politicians' and academics' interest, strikes most sub-Saharan African countries, where agriculture is the dominant activity. To face these productivity shocks in an environment where markets are imperfect, households, especially the poorest, may use child labor and cut back on education investment (Jacoby and Skoufias, 1997). This raises concerns about transmission of inequalities from one generation to the next and perpetuation of poverty. In this paper, I focus on climate and price shocks to investigate the impacts of productivity shocks on education decisions and on schooling performance.

Theoretically, this relationship is not straightforward. Productivity shocks induce an income effect and a substitution effect that move in opposite directions: a higher labor productivity increases the available income for education, but also raises the opportunity cost of education. The income effect is expected to vary with households' financial constraints and access to insurance systems. A large body of the literature finds that when households have large assets or have access to credit markets, they do not need to call on children to compensate income losses (Beegle *et al.*, 2009). In contrast, the substitution effect is likely to vary with access to the labor market. In Tanzania, (Dumas, 2015) finds that when the labor market is developed, households react to a labor productivity increase by using hired labor instead of child labor.

Ferreira and Schady (2009) conduct a literature review on the relationship between productivity shocks and education and show that negative productivity shocks worsen education investments in developing countries – in other words, education is a procyclical outcome. To capture the causal effect of productivity shocks on education, several authors focus on transitory crop shocks that reflect agricultural crises. Whether they consider pests, rodents, birds and locusts (Gubert and Robilliard, 2007), adverse weather shocks (Jensen, 2000), or drastic falls in cash-crop prices (Cogneau and Jedwab, 2012), they find that these unanticipated negative income shocks reduce school enrollment. These results indicate that the income effect outweighs the substitution effect. With this consideration in mind, a closely related question is whether the effects of productivity shocks are symmetric, so that positive shocks encourage education investments. Beegle *et al.* (2006) and Boozer and Suri (2001) find the opposite and show that larger rainfalls increase child labor, reducing school year and enrollment. By looking at the effect of coffee price increase in Brazil, Kruger (2007) also finds that positive productivity shocks hinder education.

Taken together, these empirical findings point out that the relationship between productivity shocks and schooling decisions is not necessarily linear. The first contribution of this paper is to test whether positive and negative productivity shocks hinder education. In this perspective, I consider two of the most studied shocks in the literature, weather shocks and variation in cash-crop prices. Although both of these shocks change the available incomes for education, and the opportunity cost of children's time, they may not induce the same labor demand increase in the short-run. With this difference in mind, I assess whether the nature of the shocks may explain differences in the results.

More recently, Shah and Steinberg (2017) strength the relative importance of the income and the substitution effects depending on children's age. The income effect can be particularly large for younger cohorts if they are more sensitive to variation in calories,[1] while the substitution effect may be substantially larger for the older cohorts if the opportunity cost of time evolves with age. This would explain why in India, higher wages increase human capital in early age, and decrease human capital when children are older. By exploiting the same age distinction, the second contribution of this paper is to provide a dynamic picture by looking at the effects of shocks from birth to date, and to test whether the same trend reversal is observed in the case of Tanzania.

Finally, this paper aims to assess the effect of repetition of shocks. Although households can develop strategies in the short-run to cope with income shocks, they may not necessarily manage to protect the education of their children when the shocks become recurrent. To investigate this question, I explore whether the relationship between productivity shocks and education evolves with the length of shocks.

Based on a theoretical framework with two periods, this paper discusses the underlying mechanisms behind productivity shocks in early life and in school age. Then, I use the LSMS-ISA panel survey (2008 to 2012) to examine the effect of productivity shocks on production and labor allocation decision, and I exploit the Uwezo cross section survey (2010 to 2014) in Tanzania to study the relationship between productivity shocks and education outcomes. This data set includes measures of literacy and numeracy skills and basic in-

[1] As mentioned by the literature on the fetal origins hypothesis, nutritional shocks in early life have severe and permanent consequences on educational attainment De Vreyer *et al.* (2014) and on human capital accumulation (Almond and Currie, 2011; Currie and Vogl, 2013)

formation on education status for children aged 6 to 16. These data are unique because the survey, conducted at home, reports test scores for enrolled and unenrolled children. To capture exogenous productivity variation, I focus on weather shocks and on variation in cash-crop prices. I conduct a geographically disaggregated analysis where the identification strategy exploits variation in the intensity of weather shocks and price shocks across geographical areas and over time, once I control by district, year, age, and other individual characteristics.

The main findings suggest that both commodity prices and rainfall induce an income effect by affecting the value of the production. In response to these shocks, households adapt their demand for child labor, especially when they experienced larger rainfall. Turning to education outcomes, I find no effect of current productivity shocks on the probability to dropout out of school and on the grade achievement, but positive shocks decrease schooling performances by 6-11 percent of a standard deviation. Even though children stay enrolled at school when wages go up, schooling performances drop. When I consider the repetition of shocks, I still observe that positive productivity shocks decrease schooling performances, but I also find that longer positive and negative price and rainfall shocks are detrimental to the grade attainment, implying that the relationship is not linear. The magnitude of the effects are in most cases, larger for rainfall than for prices. This discrepancy will be further analyzed. In line with Shah and Steinberg (2017), I also find that this relationship depends on the age at which the shock occurs. In early-life, the relationship is pro-cyclical since positive productivity shocks are favorable to future schooling performances.

The remainder of this paper is organized as follows: section 2 outlines the conceptual model, section 3 describes the background, the data and the shocks variables, section 4 presents the empirical strategy and the results and section 5 introduces some robustness checks.

2 Framework

In this section, I provide a simple human capital model to understand how parents allocate their children's time when there is a labor productivity shock.

I assume unitary households in which rational agents maximize their utility over two time periods. In the first period, t_1, children are too young to go to school and to work, while in the second period, t_2, children can do both activities. The parents' utility is a function of their consumption in the two periods, and of child's cognitive skills A:

$$U = U(C_1, C_2, A; X) \tag{1}$$

I consider that U is an increasing strictly quasi-concave function in C_1, C_2, and A, and add X a vector of households characteristics. Parents care about their child's cognitive skills for two possible reasons: either they have pure preferences for education, or they anticipate that education will make them better off later in life.[2] These cognitive skills are acquired according to the following production function:

$$A = \alpha A(C_1, C_2, E_2) \tag{2}$$

Where α depicts the child's learning efficiency, which depends on the child's innate ability, the child's motivation, and the parents' motivation (Glewwe, 2002). A is an increasing function of the time spent at school E_2, of consumption in early childhood C_1, and of current consumption C_2. The nutrition-learning nexus assumption is supported by the World Health Organization (WHO), which emphasizes that stunting has long-lasting consequences on the health and education of children. In t_2, parents decide to allocate total child's time T_2 between schooling attendance E_2 and labor L_{2c}[3]:

$$T_2 = E_2 + L_{2c} \tag{3}$$

In the two periods, households spending correspond to the available income I and are expressed as follows:

$$C_1 = w_1 L_{1a}(1 - \Delta) = I_1(w_1, \Delta) \tag{4}$$

$$C_2 = w_2 L_{2a} + \gamma w_2 L_{2c} + \Delta w_1 L_{1a} \tag{5}$$

Equation (5) can be rewritten as:

$$C_2 + \gamma w_2 E_2 = w_2 L_{2a} + \gamma w_2 T_{2c} + \Delta w_1 L_{1a} = I_2(w_1, w_2, \gamma, \Delta)$$

where w_1 and w_2 denote labor productivity on the farm, commonly called the shadow wage. L_{1a} and L_{2a} stand for adult labor in the two periods, and $\gamma \in [0, 1]$ is the relative

[2] If the returns to education are positive, educated children will be able to send larger transfers to their parents in the future.

[3] Child leisure is neglected but this assumption does not change the model's interpretations. Results are available upon request.

productivity of child labor compared to adult labor. Based on the literature's findings in developing countries, I assume that credit, saving and labor markets are imperfect (Jacoby, 1993; Skoufias, 1994; Chavas *et al.*, 2005; Le, 2009). Although households have no access to formal markets, I suppose they can cope with income shocks by informally saving a fraction of their income $\Delta \in [0,1]$ from t_1 to t_2. For a sake of simplicity, I first assume that Δ is does not vary with labor productivity in t_1.[4]

By substituting (2) in (1), I express household utility as a direct function of consumption and education:

$$U = U(C_1, C_2, A; X) = \tilde{U}(C_1, C_2, E_2; X) \tag{6}$$

Parents maximize their utility by choosing E_2 and L_{2c} subject to the budget constraints (4) and (5) with respect to C_1, C_2, and E_2 given w_1, w_2, γ, Δ, X and T_2.[5] The Marshallian demand functions, which depend on the relative prices and the available income $I_2(w_1, w_2, \gamma, \Delta, u)$, are written:

$$C_1 = C_1(w_1, \Delta, I_1(w_1, \Delta, u); X) = C_1(w_1, \Delta, w_1(1-\Delta)L_{1a}, u); X) \tag{7}$$

$$E_2 = E_2(w_2, \gamma, \Delta, I_2(w_1, w_2, \gamma, \Delta, u); X) = E_2(w_2, \gamma, \Delta, \Delta w_1 L_{1a} + w_2(\gamma T_2 + L_{2a}); X) \tag{8}$$

$$C_2 = C_2(w_2, \gamma, \Delta, I_2(w_1, w_2, \gamma, \Delta, u); X) = C_2(w_2, \gamma, \Delta, \Delta w_1 L_{1a} + w_2(\gamma T_2 + L_{2a}); X) \tag{9}$$

The corresponding Hicksian demand functions that minimize the total expenditure to maintain a fixed level of utility u are expressed:

$$C_1 = C_1^*(w_1, \Delta, u; X) \tag{10}$$

$$E_2 = E_2^*(w_2, \gamma, \Delta, u; X) \tag{11}$$

$$C_2 = C_2^*(w_2, \gamma, \Delta, u; X) \tag{12}$$

Based on this basic framework, I analyze how early life and current productivity shocks affect the demand for education and the schooling performance.

2.1 The effect of shocks which occur during schooling

To estimate the effect of productivity shocks which occur during schooling, I compute the partial derivatives of the Marshallian demand (8) and (9) with respect to w_2, in which I

[4] Thereafter, this hypothesis will be relaxed and discuss.

[5] I assume that, in the short-run, children's education does not change children's productivity.

substitute the Slutsky equation obtained from the Hicksian demand and the Shepherd's lemma. Thus, the effect of w_2 on the current demand for education and consumption is expressed as follow:

$$\frac{\partial E_2(w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_2} = \frac{\partial E_2^*(w_2,\gamma,\Delta)}{\partial w_2} + \frac{\partial E_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma L_{2c}+L_{2a}) \quad (13)$$

$$\frac{\partial C_2(w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_2} = \frac{\partial C_2^*(w_2,\gamma,\Delta)}{\partial w_2} + \frac{\partial C_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma L_{2c}+L_{2a}) \quad (14)$$

The first terms of the RHS stand for the substitution effects arising from the change of the relative prices between C_2 and E_2 when the purchasing power remains the same. The quasi-concavity of U entails that this first term is negative in (13) and positive in (14): when the labor productivity w_2 gets larger, education demand decreases, while consumption becomes relatively cheaper.

The particularity of this framework is that a change in the labor productivity w_2 generates two income effects. The first income effect is induced by the increase of the opportunity cost of education ($\frac{\partial E_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}E_2$ and $\frac{\partial C_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}E_2$), and the second income effect is induced by the endowment reevaluation ($\frac{\partial E_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma T_{2c}+L_{2a})$ and $\frac{\partial C_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma T_{2c}+L_{2a})$). On one hand, education becomes more expensive and reduces the available income and on the other hand, children and adults working in the fields become more productive and increase the available income. The second terms of the RHS denotes the sum of these two income effects. As a result, the total effect of a change in w_2 has an ambiguous effect on the education demand E_2, but has a positive effect on current consumption C_2.

Using (2), I can also deduce the effect of productivity shocks on cognitive skills:

$$\begin{aligned}\frac{\partial A(w_1,w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_2} &= \frac{\partial A(w_1,w_2,\gamma,\Delta,I_2)}{\partial C_2}\frac{\partial C_2(w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_2}+\\ &\quad \frac{\partial A(w_1,w_2,\gamma,\Delta,I_2)}{\partial E_2}\frac{\partial E_2(w_2,\gamma,\Delta,I_2((w_1,w_2,\gamma,\Delta))}{\partial w_2}\\ &= \frac{\partial A(w_1,w_2,\gamma,\Delta,I_2)}{\partial C_2}\left(\frac{\partial C_2^*(w_2,\gamma,\Delta)}{\partial w_2}+\frac{\partial C_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma L_{2c}+L_{2a})\right)+\\ &\quad \frac{\partial A(w_1,w_2,\gamma,\Delta,I_2)}{\partial E_2}\left(\frac{\partial E_2^*(w_2,\gamma,\Delta)}{\partial w_2}+\frac{\partial E_2(w_2,\gamma,\Delta,I_2)}{\partial I_2}(\gamma L_{2c}+L_{2a})\right)\end{aligned} \quad (15)$$

Productivity shocks have a direct positive effect on A through C_2 and an indeterminate indirect effect on A through E_2. The relative weight of the effects hinges on the form of the cognitive skills production function. In conclusion, variation in contemporaneous productivity has an indeterminate effect on education and on children's cognitive skills. It depends on the relative size of the substitution effects and the income effects, that are likely to vary with access to markets.

2.2 The effect of shocks which occur in early life

An increase in the labor productivity w_1 has a clear positive effect on the available income in t_1:

$$\frac{\partial C_1(w_1, \Delta, I_1(w_1, \Delta))}{\partial w_1} = (1-\Delta)L_{1a}$$

Thus, the saving should increase the available income in t_2 and encourage parents to send their children to school:

$$\frac{\partial E_2(w_2, \gamma, \Delta, I_2(w_1, w_2, \gamma, \Delta))}{\partial w_1} = \frac{\partial E_2(w_2, \gamma, \Delta, I_2)}{\partial I_2}\frac{\partial I_2(w_1, w_2, \gamma, \Delta)}{\partial w_1} = \frac{\partial E_2}{\partial I_2}\Delta L_{1a} \tag{16}$$

Based on this last expression and the functional form of A, I express the effect of early-life shocks on cognitive skills as follows:

$$\begin{aligned}\frac{\partial A(w_1, w_2, \gamma, \Delta, I_2(w_1, w_2, \gamma, \Delta))}{\partial w_1} &= \frac{\partial A(w_1, w_2, \gamma, \Delta, I_2)}{\partial C_1}\frac{\partial C_1(w_1, \Delta, I_1(w_1, \Delta))}{\partial w_1} + \\ &\quad \frac{\partial A(w_1, w_2, \gamma, \Delta, I_2)}{\partial E_2}\frac{\partial E_2(w_2, \gamma, \Delta, I_2(w_1, w_2, \gamma, \Delta))}{\partial w_1} \\ = \frac{\partial A(w_1, w_2, \gamma, \Delta, I_2)}{\partial C_1}(L_{1a}(1-\Delta)) &+ \frac{\partial A(w_1, w_2, \gamma, \Delta, I_2)}{\partial E_2}\frac{\partial E_2(w_2, \gamma, \Delta, I_2)}{\partial I_2}\Delta L_{1a}\end{aligned} \tag{17}$$

I deduce from this equation that early-life shocks support the educational achievement through two channels. The first channel stems from the nutrition-learning nexus: when labor productivity increases in early-life, children benefit from a better nutrition, which eases the development of cognitive skills in the long run. The second channel stems from the fact that positive productivity shocks increase the available income for education through larger transfers. Thus, in early-life, the effect of positive productivity shocks on education outcomes is positive and is not counter-balanced by any substitution effect.

If the share of saving Δ does not vary with w_1, the additional transfer induced by the productivity increase is ΔL_{1a}, but if this assumption is relaxed, the additional transfer is rewritten $\Delta L_{1a} - \frac{\partial \Delta}{\partial w_1} w_1 L_{1a}$. It is unclear whether parents increase or decrease savings with respect to labor productivity, but interpretations of the model remain the same unless parents decrease Δ such as the absolute value of the transfer becomes lower. This is unlikely because it would mean that households save less in absolute terms when they become richer. In this particular case, the effect of a productivity increase on E_2 and A_2 also become indeterminate.

3 Data

I bring together geo-referenced data from different sources to empirically test the relationship between productivity shocks and education. In this section, I present the data sources and describe the construction of the main variables.

3.1 Education and child labor data

I exploit the Uwezo dataset to measure education outcomes. The survey is a repeated cross section from 2010 to 2014 and is representative at the district level. The Uwezo program launched by the Twaweza organization seeks to collect test scores for children aged 7 to 16. By including about 100,000 children from more than 50,000 households spread over 4000 villages at each round, these data constitute a national assessment of learning. They have the strong advantage of providing test scores not only for enrolled children but also for children that have never been to school or have dropped out of school. This is not the case for most of the existing data on learning outcomes, which are available only for enrolled children. The questionnaire gathers information on children's education status. Figures A.1 and figure A.2 show that the enrollment rate reaches a maximum at age 11 and decreases afterwards, while the percentage of children who drop out keeps increasing with age, especially after 13 years old. In addition to these basic information, the data provide tests scores (table A.2 presents some descriptive statistics). These tests scores are constructed following the Pratham model[6] and are divided into two modules, the literacy test and the numeracy test. All children take the same tests that assess competencies of Standard 2 (Grade 2), a level by which children should have acquired basic reading and numeracy skills. The competencies in literacy are 1) letter recognition, 2) word recognition, 3) ability to read a sentence, 4) ability to read a paragraph and 5) text comprehension, while the competencies tested in numeracy are 1) counting, 2) number recognition, 3) ability to

[6]The Pratham model, developed by an Indian NGO, establishes a methodology to evaluate learning outcomes of young children.

rank two numbers, 4) addition, 5) subtraction and 6) multiplication. For each test, several competencies of gradual difficulties are assessed and the computed score corresponds to the highest validated competency. Figure A.3 shows that, in practice, very few children of standard 2 age validate these skills, instead most children learn them when they grow older. At each round, these scores are missing for about 2% of children. Since the percentage of missing scores remains negligible, I drop these observations.[7] Thereafter, I standardize the tests for each age-group[8] and use them as a proxy for cognitive skills. Figure A.4 depicts inequalities of test scores across districts in Tanzania in 2011.

To examine the effect of price shocks and rainfall shocks on production and labor, I use the Tanzanian LSMS-ISA (LSMS-Integrated Surveys on Agriculture) panel data, which consist of three rounds (2008-2009, 2010-2011 and 2012-2013). The survey was designed to be nationally representative and covers the entire country. The location of households is given by village coordinates. Due to the high split-off and the low attrition rate, 3,265 households were interviewed in 2008, 3924 in 2010 and 5,015 in 2012. These data are relevant for this analysis because they gather information on the value of the household production, and on children's activities at the individual level. To study the effect of shocks at the extensive and at the intensive margin, I consider whether the child has ever worked in the 12 months preceding the survey, the number of days of labor performed in the fields over this period, and the working occupation during the week before the survey. The LSMS datasets also provide appropriate information on current education decisions (enrollment and dropping out) and on education outcomes resulting from successive education decisions (grade achievement). Table A.1 presents more descriptive statistics on education and child labor from 2008 to 2012.

3.2 Climate data

Tanzania is an agriculture-based country where 80 % of the population lives in rural areas and where agriculture consitutes to half of the GDP. This dependency makes Tanzania vulnerable to many production shocks. Among these shocks, climate shocks constitute one of the main risks that farmers face. The Center for Global Development classifies countries according to their climate change vulnerability, and ranks Tanzania at the 20th most vulnerable in the world out of 55 countries (Wheeler, 2011). The low diffusion of

[7] I may encounter a selection bias if missing scores are not random. To address this issue, I impute a score and I find that results are not sensitive to the inclusion of children with imputed test scores. Results are available upon request.

[8] I compute the deviation from the mean at each wave by age.

irrigation systems (FAO, 2009) makes households even more sensitive to weather variations over time. Basalirwa *et al.* (1999) delineated 15 homogenous groups in Tanzania based on climatic conditions and topographic features. With this high number of agro-ecological areas, the intensity and type of climate shocks are also expected to vary across geographical areas.

To investigate the impact of climate shocks, I complement the dataset with monthly data from the Standardized Precipitation Evapotranspiration Index (SPEI), gridded by longitude and latitude lines with a degree of precision of 0.5.[9] In the literature, most authors focus on the Standardized Precipitation index (SPI) (Rosenzweig and Udry, 2014; Jensen, 2000). This indicator, based only on precipitation data, assumes that droughts are particularly sensitive to temporal precipitation variations and that other climate variables are stationary. As a consequence, the SPI neglects the effects of global warming on production even though temperature has severe consequences on the drought intensity. As Vicente-Serrano *et al.* (2012) underlined, it implies that rainfall data are not necessarily suitable to predict crop yield. Indeed, the growing cycle of a plant does not depend only on the rainfall quantity but, most importantly, on the evapotranspiration of water.[10] This evapotranspiration varies with the temperature and explains why the same quantity of rainfall can have a different impact on the severity of droughts.

Crop seasons and climatic shocks

I compute climate indicators for the time period that matters the most for the plants' growing cycle (Harari and La Ferrara, 2014). According to Kubik and Maurel (2016), weather conditions from March to May constitute the most relevant period at explaining Tanzanian crop production.[11] An alternative is to use the average value of SPEI from January to June.[12] To capture different types of droughts, I construct several SPEI variables from March to May: 6-month $SPEI_{6mm}$ and 12-month $SPEI_{12mm}$ (see appendix A for more details). As a robustness check, I also exploit the traditional rainfall data from NOAA. To examine the non-linearity of climatic conditions, I define positive and negative rainfall shocks, denoted PR and NR. I consider that there is a drought when the SPEI is lower than 0.5 standard deviations, and that there is a positive rainfall shock when the SPEI is larger

[9] These data have been developed by Vicente-Serrano *et al.* (2010).

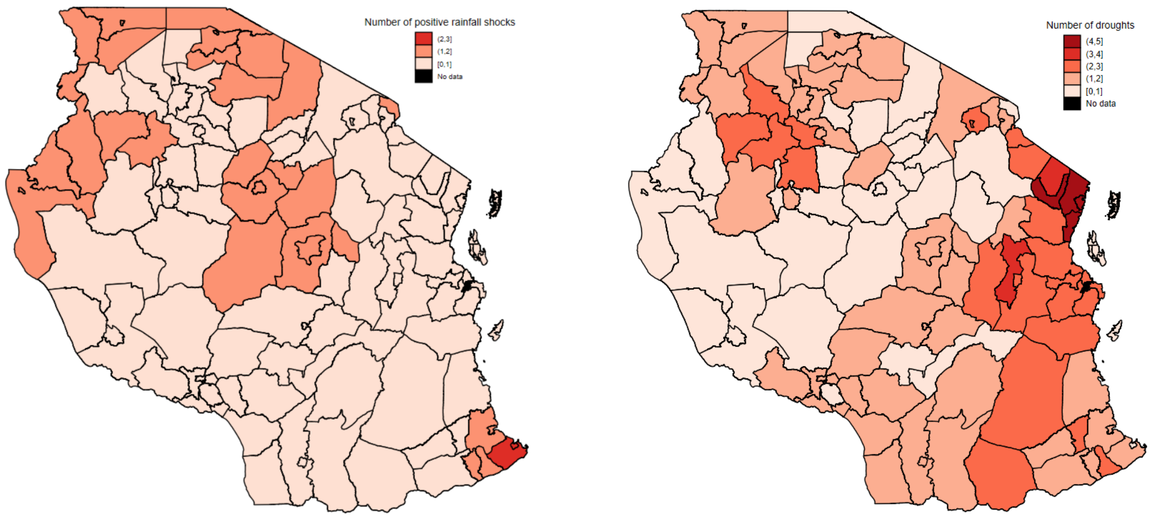
[10] The evapotranspiration occurs through two mechanisms : the evaporation of water from the soil and the transpiration of crops.

[11] This period, called "Masika", corresponds to the long rainy season in bimodal areas and to the rainy months in unimodal areas.

[12] Results are very similar and are available upon request.

than 0.5 standard deviations.[13] This construction implies that positive values of the SPEI stand for better productivity conditions.[14] Figure 1 depicts the distribution of negative and positive rainfall shocks for the period that covers the two datasets.

Figure 1: Number of rainfall shocks between 2008 and 2014.



(a) Positive rainfall shocks

(b) Negative rainfall shocks

Sources: SPEI data.

3.3 Price data

Incomes from agricultural activities should also be responsive to international price variations. From the Arusha Declaration in 1967 to 1980, prices were centrally controlled by the government (Msambichaka *et al.*, 1983). But from 1980 onwards, the market was liberalized and deregulated (Msambichaka *et al.*, 2006). The objective of this policy was to ensure a competitive, efficient and equitable market. Today, this food market deregulation implies that international price volatilities influence prices at which farmers sell their commodities on the local market. Notwithstanding, most crops are still exclusively produced for self-consumption. Consequently, the transmission channel between international prices and producers should exist only for producers of cash-crop commodities. Thus, I consider only price variations of the main cash-crops produced in Tanzania: cotton, coffee, coconut, tobacco, tea, sugar and palm-oil. Since Tanzania holds a small share of the market for these crops, international prices should be exogenous and independent of the Tanzania's

[13]By taking these thresholds, about 20 % of the LSMS and Uwezo household samples are affected by droughts and about 20 % are affected by positive rainfall shocks.

[14]Since the SPEI is standardized with respect to local historical trends, positive values do not mean that there is an excess of water but only that rainfalls are larger than the historical trends.

production.

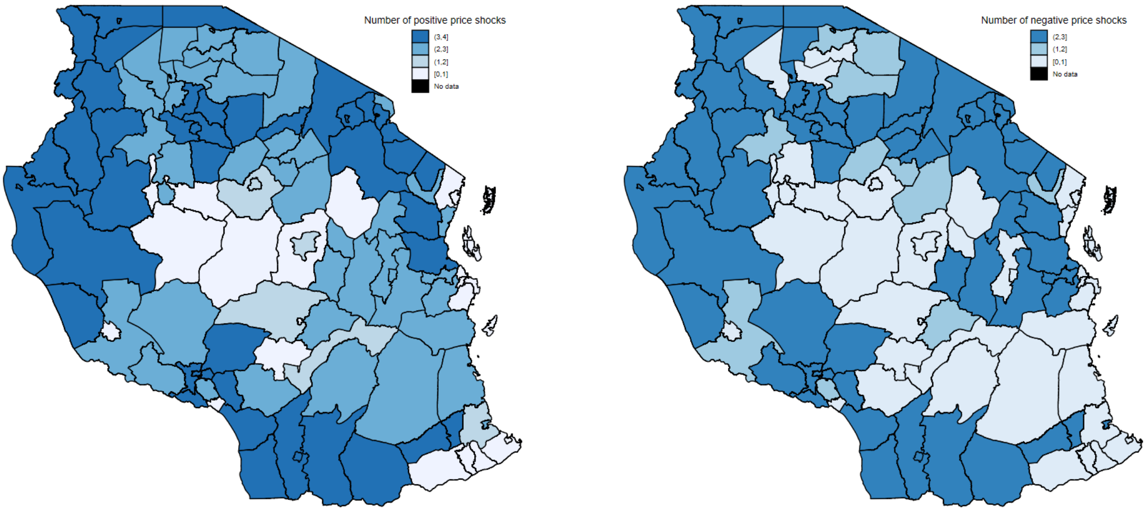
To measure volatility in international prices, I exploit the data from the World Bank Commodities Price Data and I use annual prices expressed in 2010 US $ per kg. To obtain an aggregate price index, the FAO computes a weighted value of food prices. In order to come up with a price index which is representative of the Tanzanian market, I adopt the same strategy and construct a price index P_{jy} based on the main Tanzanian cash-crop commodities. Since geographical areas do not produce the same commodities and are not similarly affected by price variations (Dube and Vargas, 2013; Imbert *et al.*, 2016), I weight price variations by the percentage of land allocated to cash-crop c in location j in 2000 $L_{c,j,2000}$:

$$P_{j,y} = \sum_{c=1}^{n} \frac{(p_{c,y} - T_{c,y})}{T_{c,y}} * L_{c,j,2000}$$

$\frac{(p_{c,t} - T_{c,t})}{T_{c,t}}$ is the deviation from the trend in percentage. The agricultural intensity, $L_{c,j,2000}$, is computed from the geo-coded EarthStat data that combine satellite land cover data and agricultural census. These data provide the size of lands allocated to each crop with a 10km by 10 km resolution.[15] As a result, the price index varies over time and across locations. As a robustness check, I construct this index at the household level by using the LSMS data. The area of land allocated to each crop at the household level might be endogenous, but this index has the advantage of capturing an individual exposure to price shocks. To assess the non-linearity in prices, I define negative and positive price shocks (NP and PP) by referring to the first and the last quantiles, respectively. The repartition of price shocks is represented in Figure 2.

[15] 2000 is the most recent year for which these data are available with this level of precision.

Figure 2: Number of price shocks between 2008 and 2014.



(a) Positive price shocks

(b) Negative price shocks

Sources: World Bank Commodities Price data, and EarthStat data.

4 Estimation strategy and results

4.1 Mechanisms

To understand how households take their education decisions when they are exposed to climate and price shocks, I first study the underlying channels at play with the following specification:

$$Y_{hjy} = \beta_0 + \beta_1 PR_{j,y} + \beta_2 NR_{j,y} + \beta_3 PP_{j,y} + \beta_4 NP_{j,y} + \gamma X_{hjy} + \delta_j + \nu_y + \epsilon_{hjy} \tag{18}$$

Where the subscript h depicts the household, j the location, and y the year of the survey. To test whether climate and price shocks translate into productivity shocks, I examine the effect of shocks on two outcomes Y_{hjy}, household production and household labor decisions.

After controlling by household, district, year fixed effects, and by the quantity of labor performed, Table 1 shows that a negative rainfall shock decreases the production by 35 percent, while a positive price shock increases the production by 60 percent, respectively. Results are very similar when prices are defined at the district level (table A.3), when I consider different rainfall data sources, and when the rainfall variable is computed from different periods (table A.4).

To analyze the effect of climate and price shocks on production, it is necessary to remind an obvious but substantial difference. Climate shocks are expected to increase the quantity

Table 1: Effects of productivity shocks on the log of Household Production.

	(1)	(2)
Positive Rainfall Shock$_{j,y-1}$	0.209	0.139
	(0.192)	(0.151)
Negative Rainfall Shock$_{j,y-1}$	-0.569***	-0.378***
	(0.211)	(0.143)
Positive Price Shock$_{i,j,y-1}$	1.357***	0.579***
	(0.196)	(0.214)
Negative Price Shock$_{i,j,y-1}$	0.489**	-0.056
	(0.212)	(0.183)
R-squared	0.301	
Within R-squared		0.106
Observations	7,904	7,904
Localities and Times F.E	×	×
Households F.E		×

Sources: LSMS-ISA from 2008, 2010 and 2012. Note: Production is computed in Tanzanian shillings (TZS). Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the number of days of labor in the field, and the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

of harvested crops, while prices raise the value of the production without necessarily changing the quantity produced. This entails that rainfall is more likely to increase the labor intensity in the fields than price variation. The results of the effect of productivity shocks on child labor confirms this conjecture.

In table 2, I estimate the effect of shocks on the probability to work, and on the working status the week prior the survey of children aged 6 to 16 who belong to farming households. A positive rainfall shock increases the probability to work in all sectors, while a negative rainfall shock decreases the probability to work in all sectors and in agriculture by 4.4 % and 6.3 %, respectively. To investigate the effect of shocks at the intensive margin, I estimate the effect of productivity shocks on the number of days of labor performed by all children in the household, and I find that a positive rainfall shocks increases the demand for child labor while a negative rainfall shock induces the opposite effect. In comparison, price shocks have no significant impact (see Table A.5). Turning to continuous standardized variables, the results in Table 3 suggest that an increase of one standard deviation of rainfall and price increase the number of days of labor performed by children in the households by 38 days and 12 days, respectively. This discrepancy between rainfall and prices may have several explanations. First, households may take more time to perceive and react to price variation

Table 2: Effects of productivity shocks on the probability of working the week prior the survey.

	(1) Work	(2) Paid	(3) Unpaid	(4) Agriculture	(5) Domestic
Positive Rainfall Shock$_{j,y-1}$	0.062**	0.004	-0.011	-0.025	0.000
	(0.029)	(0.007)	(0.012)	(0.024)	(0.020)
Negative Rainfall Shock$_{j,y-1}$	-0.044**	-0.005	0.005	-0.063***	-0.024
	(0.020)	(0.005)	(0.018)	(0.018)	(0.017)
Positive Price Shock$_{i,j,y-1}$	-0.028	0.008	-0.031	0.011	-0.030
	(0.034)	(0.008)	(0.022)	(0.038)	(0.030)
Negative Price Shock$_{i,j,y-1}$	0.009	-0.006	0.006	0.032	0.002
	(0.031)	(0.006)	(0.022)	(0.031)	(0.026)
Within R-squared	0.099	0.032	0.550	0.075	0.081
Observations	12,674	12,788	12,788	12,788	12,788
District and Year F.E	×	×	×	×	×
Households F.E	×	×	×	×	×

Sources: LSMS-ISA from 2008, 2010 and 2012. Notes: standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

than rainfall variations. Indeed, households might not be aware of the exact price of each cash crops before selling them in the market. Second, they probably have less room to adapt their demand for labor. A rainfall increase may encourage households to provide more labor, while in case of a price increase, household also need to adapt their quantity of labor, but in a smaller extent. Interestingly, when the price index is constructed from subsistence crops,[16], the effect of prices is two times smaller. This is not surprising because when subsistence crops become more expensive, the value of the households production increases but this does not translate necessarily in an opportunity loss since most products are self-consumed.

Overall, these results lead to think that parents are encouraged to increase child labor to benefit from productivity variation, especially when they experience rainfall variation.

4.2 Effect of current productivity shocks

In this section, I present the estimation strategy that identifies the effect of productivity shocks on education outcomes, and I deduce from these reduced forms whether the substitution effect or the income effect empirically prevails.

The effect of current shocks on education outcomes is estimated with the following

[16] maize, sorghum, wheat, and groundnut

Table 3: Effect of climate and aggregate price variables on days of labor in the field (beta coefficients)

	(1)	(2)
SPEI-6 months March-May	37.74***	38.01***
	(11.36)	(11.42)
P_{ijy-1}	11.77***	
	(4.474)	
P_{ijy-1} subsistence crops		6.478*
		(3.337)
Within R-squared	0.054	0.062
Observations	5,257	5,257
Localities and Time F.E	×	×
Household F.E	×	×

Sources: LSMS-ISA from 2008, 2010 and 2012. Notes: Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the number of adults and the number of children in the household and the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

specification:

$$E_{ijty} = \beta_0+\beta_1 PR_{j,y-1}+\beta_2 NR_{j,y-1}+\beta_3 PP_{j,y-1}+\beta_4 NP_{j,y-1}+\gamma X_{ijy}+\delta_j+\mu_t+\nu_y+\epsilon_{ijty} \quad (19)$$

where i denotes the child of age t living in district j during the survey year y. The parameters δ, μ and ν are district, age and year fixed-effects, respectively. The error term ϵ_{ijty} is clustered by district, and X_{ijy} is a set of household controls such as the number of adults and children in the household, the number of boys among siblings, and age and education of the household head. E_{ijty} is a large set of education outcomes that measures education status and educational achievement. I regress current education outcomes E_{ijty} on the lagged climate variable $SPEI_{j,y-1}$ and on the lagged aggregated price index $P_{j,y-1}$, because the schooling calendar starts in January in Tanzania.

By adding region and year fixed effects, this estimation strategy compares children from the same location in different rounds of the survey. It captures the causal effect of productivity shocks on education outcomes if several assumptions are satisfied: 1) $SPEI_{j,y-1}$ and $P_{j,y-1}$ should change the labor productivity (see sub-section 4.1), 2) the shocks should be purely exogenous (see sub-section 3.2 and 3.3 for further discussion) and finally 3) the shocks should not be correlated with unobserved variables that would explain education outcomes. This question will be addressed later in section 5.

To estimate the effect of productivity variations on children's education (whether the child has dropped out of school and what is the highest grade achieved), I use the large Uwezo data and I restrict the sample to school aged children, aged 7 to 16. In Table 4, I observe that neither positive nor negative productivity shocks change the educational attainment or the probability to stay enrolled in school status. Even though these shocks do not provoke erratic attendance, they may decrease children's schooling performance if children work and spend less time at school. To test this hypothesis, I use and I regress test scores on price and climate shocks.

Table 4: Effect of current productivity shocks on schooling performances

	Dropout	Grade
Positive Rainfall in y-1	-0.0052	-0.0075
	(0.0052)	(0.0347)
Negative Rainfall in y-1	0.0024	0.0025
	(0.0039)	(0.0206)
Price in y-1	0.0065	-0.0292
	(0.0057)	(0.0385)
Negative Price in y-1	0.0153**	-0.0314
	(0.0073)	(0.0325)
R-squared	0.0394	0.6821
Observations	326,666	287,300
Localities F.E	×	×
Year F.E	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table 5 presents the results and shows that only positive rainfall and price shocks decrease Swahili and maths scores, and they do so by 0.06-0.11 standard deviations. The effect of a positive rainfall shock is slightly larger and more robust than the effect of a positive price shock, probably because they do not induce the same substitution effect in the short-run.

If parents are more willing to drop their less performant children from school in case of positive shocks, enrolled children are positively selected. However, when I restrict the sample to enrolled children (columns (3) and (4)), results are not statistically different meaning that the selection bias is limited.

Table 5: Effect of current productivity shocks on schooling performances

	(1) swahili	(2) maths	(3) swahili	(4) maths
Positive Rainfall in y-1	-0.0599***	-0.1122***	-0.0608***	-0.1058***
	(0.0220)	(0.0337)	(0.0224)	(0.0348)
Negative Rainfall in y-1	0.0543*	0.0041	0.0421	0.0029
	(0.0305)	(0.0311)	(0.0264)	(0.0244)
Positive Price in y-1	-0.0499	-0.1058**	-0.0142	-0.0660*
	(0.0493)	(0.0512)	(0.0412)	(0.0378)
Negative Price in y-1	0.0253	0.0087	0.0485	0.0442
	(0.0466)	(0.0525)	(0.0389)	(0.0422)
R-squared	0.3545	0.3242	0.3535	0.3179
Observations	326,666	326,666	292,343	292,343
Localities F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

The effect of productivity shocks may also vary with households' wealth. On one hand, the substitution effect should be larger for poor households if they have a higher marginal utility of consumption and have larger incentive to drop their children out of school when education becomes more expensive. On the other hand, the income effect is larger for rich households who own more lands and assets. Thus, it is not clear whether rich households react more to productivity shocks than poor households. To explore this heterogeneity, I compute the household consumption following the guideline of Deaton and Zaidi (2002).[17] Table A.6 and A.7 shows that positive productivity shocks are detrimental for test scores at all wealth levels, but the magnitude of the effect is larger for the poorest households.

In addition, Table A.8 and A.9 show that the effects of positive shocks on labor and education decisions are also very close for boys and girls and are not statistically different.

I also examine whether the effects are heterogeneous across children's age by splitting school-aged children in two sub-groups, primary-aged children, and secondary-aged children. If older children are more productive and have a larger work capacity, the substitution effect will be larger. However, contrary to the primary education, the secondary school is

[17]This consumption variable is composed of four sub-aggregates, food items, non-food items, housing consumption and consumer durables. In order to create a consumption variable independent from current shocks, I exclude all current consumption items such as food consumption and current non-food items that could have been affected by productivity shocks.

not mandatory and tuition fees are charged.[18] Thus, households sending their children to secondary schools are likely to be richer, to have stronger preferences for education, and to be less reactive to productivity shocks. In conclusion, it is not clear whether the substitution effect will be larger for the older cohort but this discrepancy can be empirically tested. I see from Table A.10 and Table A.11 that results are not statistically different between age cohorts.

Beyond the age, the position within the sibling matters if parents systematically call on the eldest or on the youngest child. In Table A.12, I restrict my analysis to families with more than one child and test whether eldest children are more affected by shocks, and I find that the eldest turns to be less affected. A possible explanation of this finding is that the eldest works whatever the productivity conditions, while younger children constitute the adjustment variable. but I do not find such pattern.

To go further in the analysis, I also test whether these effects vary with the agricultural intensity of the district. To do so, I interact every shock with the percentage of cultivated land by district. Results presented in Table A.13 show that the effect of positive price and positive rainfall shocks are robust, but that the effect of a positive rainfall shock tends to fade with the agricultural intensity. In contrast, negative rainfall shocks improves Swahili test scores, but this effect disappears with the agricultural intensity. Indeed, households may need less labor in case of drought, but only in districts where agriculture is not intensive.

According to the model's predictions, all these results indicate that contemporaneous productivity shocks have a counter-cyclical effect on schooling performance, and that the substitution effect dominates the income effect ($\frac{\partial A(w_2,\gamma,\Delta,I_2(w_1,w_2\gamma,\Delta))}{\partial w_2} < 0$).

4.3 Effect of the length of shocks

To study whether positive productivity shocks are more detrimental to education when they become more frequent, I compute for each child the length of shocks, defined as the maximum number of consecutive shocks from the beginning of primary education (at 7 years old) to the year of the survey:

$$E_{ijty} = \beta_0+\beta_1 \sum_{i=7}^{y} PR_{j,i}+\beta_2 \sum_{i=7}^{y} NR_{j,y}+\beta_3 \sum_{i=7}^{y} PP_{j,i}+\beta_4 \sum_{i=7}^{y} PP_{j,y}+\gamma X_{ijy}+\delta_j+\mu_t+\nu_y+\epsilon_{ijty} \quad (20)$$

[18] According to UNESCO (2013), secondary education fees were between 30,000 and 40,000 TSH in 2009, which amounts to half of the average Tanzanian monthly wage.

The specification is similar than equation (19) except that I am interested in the repetition of shocks on education outcomes that capture current decisions as well as prior decision (the grade achievement and the probability of being late.

Table 6 reports the main results and suggests that the effect of productivity shocks on education attainment is non-linear. Indeed, when these shocks last longer, both positive and negative productivity shocks have a negative effect on the grade achievement, meaning that a larger share of children are likely to stay enrolled in school but repeat a year. However, the comparison of the coefficient informs that rainfall shocks have larger effects than price shocks, and that postive shocks are more detrimental than negatives ones.

Table 6: Effect of shocks during schooling on education status.

	Grade	Overage
Length positive climate shocks	-0.1195***	0.0248***
	(0.0148)	(0.0044)
Length negative climate shocks	-0.0839***	0.0094**
	(0.0249)	(0.0046)
Length positive price shocks	-0.0855***	0.0104**
	(0.0280)	(0.0040)
Length negative price shocks	-0.0313***	0.0056**
	(0.0108)	(0.0026)
R-squared	0.6178	0.2169
Observations	316,283	328,948
District F.E	×	×
Year F.E	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

To investigate the effect of shocks on cognitive skills, I turn to the effect on test scores. Results presented in Table 7 give evidence that positive climatic and positive price shocks during school age reduce schooling performance in math and Swahili ($\frac{\partial A(w_1,w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_2} < 0$).

Thus, the results advocate that educational achievement is probably reduced due to lower time investment in school or in doing homework. This last channel cannot be tested since the time spent at school is not available in the datasets. This emphasizes the need for data that gather test scores and detailed information on children's time allocation.

Table 7: Effect of Shocks during schooling on Test Scores

	Swahili	Maths	Swahili	Maths
Length positive climate shocks at 7	-0.0761***	-0.0628***	-0.0739***	-0.0555***
	(0.0109)	(0.0165)	(0.0105)	(0.0158)
Length negative climate shocks at 7	0.0250	0.0033	0.0301*	0.0134
	(0.0187)	(0.0189)	(0.0179)	(0.0183)
Length positive price shocks	-0.0232	-0.0519***	-0.0183	-0.0468**
	(0.0161)	(0.0194)	(0.0173)	(0.0201)
Length negative price shocks at 7	0.0114	0.0143	0.0170	0.0171
	(0.0118)	(0.0134)	(0.0123)	(0.0136)
R-squared	0.3583	0.3264	0.3574	0.3203
Observations	328,948	328,948	294,521	294,521
District F.E	×	×	×	×
Year F.E	×	×	×	×
Sample	All	All	Attend	Attend

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

4.4 Effect of early shocks

In order to shed light on early life shocks' consequences, I estimate the following equation:

$$E_{ijty} = \beta_0 + \beta_1 \sum_{t=birth}^{6} NR_{j,t} + \beta_2 \sum_{t=birth}^{6} NP_{j,t} + \beta_3 \sum_{t=birth}^{6} PP_{j,t} + \beta_4 \sum_{t=birth}^{6} NP_{j,t} + \gamma X_{ijt} + \delta_j + \mu_t + \nu_y + \epsilon_{ijty} \tag{21}$$

I look at the effect of positive and negative price and climate shocks occurring from birth to 6. Table 8 presents the main results and shows that both positive rainfall and price shocks which occur in early life increase the grade achievement and reduce the probability of being late. More surprisingly, negative rainfall shocks also increase the education attainment.[19]

I also check whether early life shocks have long-lasting consequences on schooling performance of children that are currently of school age. Since test scores of children aged 0 to 6 are not available, short-run effects of early life shocks cannot be estimated. This being so, long-run effects constitute a lower bound of short-run effects if early-life effects fade over time. Consistently with the last results, Table 9 shows that positive price shocks from birth to six years old are pro-cyclical and have positive significant impacts on Swahili and math scores ($\frac{\partial A(w_1,w_2,\gamma,\Delta,I_2(w_1,w_2,\gamma,\Delta))}{\partial w_1} > 0$). However, positive rainfall shocks have no

[19] This result has no theoretical ground but can be explained by selection issues if droughts in early life increase the mortality rate of the most vulnerable children.

Table 8: Effect of Early Life Shocks on children's activities

	Grade	Overage
Nb. pos. climate shocks from birth to 6	0.0667***	-0.0172***
	(0.0160)	(0.00429)
Nb. neg.. climate shocks from birth to 6	0.0220	-0.00513
	(0.0166)	(0.00356)
Nb. pos. price shocks from birth to 6	0.0858***	-0.0360***
	(0.0207)	(0.00489)
Nb. neg. climate shocks from birth to 6	0.0447**	-0.0204***
	(0.0178)	(0.00411)
R-squared	0.665	0.237
Observations	259,689	295,879
District F.E	×	×
Year F.E	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

significant effect. As the conceptual framework asserts, shocks in early childhood affect education through two possible channels. The first channel is the nutrition-learning nexus, which suggests that positive productivity shocks are likely to improve children's nutrition in early life, stimulate children's growth, and have long-lasting impact on children's cognitive skills. Second, a better labor productivity allows parents to transfer larger savings in absolute value, which can be used to protect education against current income shocks.

To investigate the channel between productivity shocks and children's health, I exploit the LSMS data and construct a z-score of height for age based on the 2006 WHO child growth standards (Leroy, 2011). This index measures the prevalence of stunting among children from 0 to 5. Table 10 shows that, consistently with the model's expectations, children appear in better health when the labor productivity is improved: at birth, an increase of the climate variable by one standard deviation raises the Z-score of height for age by 0.4 point. Similarly, at one year old, an increase of the climate and the price variable by one standard deviation raises the Z-score by 0.2 and 0.05, respectively. When children are older than 2 year old, these effects become insignificant.

In conclusion, these results are consistent with the literature (Almond and Currie, 2011; Currie and Vogl, 2013; Shah and Steinberg, 2017) which finds that early life shocks have long-lasting consequences on the grade attainment and on schooling performance.

Table 9: Effect of Early Life Shocks on Schooling Outcomes

	Swahili	Math
Nb. pos. climate shocks from birth to 6	-0.00343	-0.00858
	(0.0111)	(0.0123)
Nb. neg. climate shocks from birth to 6	0.0125	0.00724
	(0.0123)	(0.0133)
Nb. pos. price shocks from birth to 6	0.0296**	0.0257*
	(0.0116)	(0.0133)
Nb. neg. price shocks from birth to 6	-0.00559	-0.0193
	(0.0128)	(0.0155)
R-squared	0.358	0.327
Observations	328,948	328,948
District F.E	×	×
Year F.E	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table 10: Effect of climate and price variations on Z-score of height for age (beta coefficients).

Age	0	1	2	3	4	5
$P_{i,j,y}$ aggregate_cash_fao	0.004	0.046*	-0.093	0.008	-0.039	0.038
	(0.040)	(0.026)	(0.092)	(0.032)	(0.032)	(0.033)
$SPEI_{j,y}$	0.387***	0.178**	-0.074	-0.077	0.053	0.098
	(0.146)	(0.082)	(0.074)	(0.070)	(0.090)	(0.083)
Within R-squared	0.086	0.032	0.062	0.030	0.089	0.048
Observations	1,294	1,304	1,406	1,304	1,360	1,278
Localities and Times F.E	×	×	×	×	×	×
Households F.E	×	×	×	×	×	×

Sources: LSMS-ISA from 2008, 2010 and 2012. Notes: standard errors, clustered by geographical units ($0.5°\times0.5°$ of precision), are reported in parentheses. Controls are survey month dummies, age dummies and years of the survey. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

5 Discussion

In this analysis, climate and price shocks affect education decisions and schooling performance by changing households resources and the opportunity cost of children's time. However, the causal impact is identified only if the shocks do not influence education through other channels. In this section, I discuss potential sources of bias.

First, shocks should not influence the perceived returns to education which enter the education decisions. This kind of general equilibrium effect may happen when the shocks persist over time. Since this analysis focuses on shocks that persist only for relatively short periods of time, it is very unlikely that the shock of interest, current and school-age shocks, change the returns to education.

Another concern that is selective migration. If households who move towards prosperous locations have specific characteristics, children in districts that experienced positive productivity shocks may be selected. In other words, when estimating the effect of positive productivity shock, the migration selection may induce a bias, and misleads the interpretation. To investigate whether it is an empirical issue, I regress the probability that a child aged 7 to 16 migrates in another district on lagged positive and negative productivity shocks.[20] Results presented in Table A.14 suggest that this selection bias is negligible and that productivity conditions do not significantly drive children's migration.

As Shah and Steinberg (2017) emphasize, mortality in early childhood also represents a potential source of bias. Indeed, exposure to negative productivity shocks such as drought may increase mortality in early life and change the composition of sampled children. Surviving children, who are more resistant, are likely to be positively selected and to better perform at school. Consequently, the results confound the direct effect of shocks on education and the effect from selection mortality. To address this concern, I use the LSMS data that provide the number of individuals, including infants, who died over the past two years. Then, I test whether mortality of children aged 0 to 6 years old depends on productivity shocks. Table A.14 reports no significant effect suggesting that mortality does not bias the results.[21]

Last, but not least, results are biased if productivity shocks affect the quality of education. Heavy rains for instance, may make roads impassable, damage access to water or other services at school, and increase teachers' absenteeism. By changing the attractiveness

[20] Internal migration concerns 6 % of children from this age group.

[21] Results are similar when I restrict the analysis to the mortality rate of children younger than 3 years old.

of agricultural activities, productivity shocks are expected to select teachers, but is unclear whether positive productivity shocks especially attract skilled or unskilled teachers.

To test these channels, I estimate the effect of productivity shocks on the percentage of teachers who attend school at the date of the survey, on the percentage of qualified teachers, and on the access to water at school. As Results in Table A.15 show that productivity conditions does not significantly drive the quality of education, putting aside the effect of droughts on the absenteeism rate. In case of a negative rainfall shock, the teachers' absenteeism rate decreases by 1.2 %, probably because labor in the fields is less attractive.

To estimate the effect of productivity shocks on education status, I have exploited the large Uwezo data set. Instead of adopting a panel-location analysis, I can also use the LSMS data and add households fixed effects in the estimations. This specification should produce the same results, except that the estimations are identified using households with more than one child. If parents react to one child's shock exposure by reallocating resources within the household, the households specifications should be different from the district specifications (Shah and Steinberg, 2017). However, I rule out this hypothesis by showing that estimations with households fixed effects are qualitatively similar (see Table A.16).

6 Conclusion

In this paper, I study the effect of labor productivity on the demand for education and on schooling performance in Tanzania. To capture exogenous variations in labor productivity, I use a combination of geo-coded data to identify variations in climate conditions and in cash-crop prices over time and across location.

The core of this analysis is to investigate the effect of productivity shocks on children's education by considering two particular aspects, the age at which shocks occur, and the length of shocks.

The first findings support the idea that early life productivity shocks (from birth to 4 years old) are favorable to the development of future cognitive skills. Based on the theoretical model, this relationship is explained by two channels. Higher labor productivity in early-life improves children's nutrition and allows parents to save money to finance education later in life.

In contrast, when children are of school age, the relationship between positive productivity shocks and education becomes counter-cyclical. This result, close to Shah and Steinberg (2017) findings, suggests that the substitution effect outweighs the income effect. When children are of school age and can work, positive productivity shocks increase the available income for education, but also increase the labor productivity which encourage households to call on child labor.

Interestingly, the effects also vary with the length of shocks.

In response to current positive productivity shocks, households increase child labor, but keep their children at school. Schooling performance performance significantly drop, but the grade attainment remains the same. In other words, productivity shocks are detrimental to schooling performance even when children stay enrolled in school. This emphasizes that limiting the analysis to education enrollment is not satisfactory. To test whether the results are due to erratic attendance, detailed data on children's schedule are needed. However, when shocks become recurrent, both positive and negative shocks lower the education attainment, but the effects of negative productivity shocks are smaller and are not translated into a decline in test scores.

In terms of public policies, these results imply that it is necessary to alleviate tuition fees, but also to account for the opportunity costs of children's time. In this regard, it would be interesting to test whether access to labor market allows households to cope with positive shocks. This research question, which requires rich data on the labor market, is left for future research.

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A Construction of the Standard Precipitation Evapotranspiration Index (SPEI)

To account for several climatic parameters, the SPEI provides a simple drought measure defined by the difference D between the original SPI and the Potential Evapotranspiration (PET). The PET corresponds to the evapotranspiration that would occur if the surface was sufficiently watered to be green and to have an active growth. Naturally, this PET varies between locations and depends on climate conditions and on the nature of the soil. This index is not observed and has to be modelled. The most wide-known computation used in the SPEI data is the Penman-Monthei equation.[22] Therefore, D represents the monthly water surplus or water deficit.

Similarly to the SPI, the SPEI accounts for different time scales that determine the nature of droughts. Short time scales represent soil water content and discharge in headwaters, while medium time scales refer to storage of water sources and long-time scales illustrate variations in groundwater. The various time scales are computed difference D by aggregating various time periods. For instance, the 6-month SPEI index is measured by adding the D values of the last 5 months before the current month.[23]

Then, to obtain comparable SPEI values in time and in space, the SPEI index is standardized using the Log-Logistic distribution. By construction, the historical mean is 0 for each geographical cell and the SPEI index is expressed in units of standard deviation from the historical average.

[22] According to the FAO manual on crop evapotranspiration (Allen *et al.*, 1998), the FAO-56 Penman-Monteith equation estimates a reference evapotranspiration Et_0 and is the most efficient method to approximate the PET:

$$Et_0 = \frac{0.408(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34 u_2)}$$

Where R_n is the net radiation of the crop surface, G, the soil heat flux density, T the mean daily air temperature at 2 m height, u_2 is the wind speed at 2 m height, e_s is the saturation vapour pressure, e_a is the actual vapour pressure , Δ is the slope vapour pressure curve and γ is the psychrometric constant.

[23] To give a decreasing weight of the data from the past, Vicente-Serrano *et al.* (2010) adopt a Gaussian kernel function.

B Descriptive statistics

Table A.1: Descriptive statistics from the LSMS-ISA data

Year	2008	2010	2012
Composition of samples			
Number of districts	126	128	131
Number of wards	87	103	108
Number of HH	3265	3921	5004
Number of children	4512	5239	6236
Household characteristics			
Number of adults	3.208	3.425	3.511
Number of children	3.315	3.321	3.305
Household production (TSH)	228545.4	357620.8	566570.5
cultivated area (acres)	4.822	4.548	5.759
Children characteristics			
Child's age	11.407	11.370	11.335
Child is female	0.507	0.503	0.507
Child is enrolled in school	0.815	0.883	0.858
Number of completed grade	4.295	4.388	4.324
Child dropout school this year	0.043	0.050	0.061
Child has repeated a grade this year	0.123	0.117	0.129
Child works last year	0.115	0.231	0.262
Number of days of labor in the field	73.554	73.200	89.835

Table A.2: Descriptive statistics from the Tanzanian Uwezo survey..

Year	2010	2011	2012	2013	2014
Composition of samples					
Number of districts	42	131	124	129	45
Number of villages	1077	3825	3752	3844	1313
Number of HH	18098	57945	56106	52808	16013
Number of children	35540	110435	105352	104162	32694
Household and children characteristics					
Size of households	7,156	7,284	7,016	6,672	7,040
Household is poor	0,815	0,816	0,781	0,775	0,593
Household is ultra poor	0,320	0,335	0,306	0,301	0,162
Number of children	5,474	2,797	2,761	3,197	3,523
Child's age	11,354	11,187	11,167	11,162	11,062
Child is female	0,507	0,502	0,497	0,496	0,495
Child is enrolled in school	0,897	0,886	0,884	0,880	0,796
Number of completed grade	4,184	4,018	3,950	4,101	3,091
Child drops out school this year	0,053	0,056	0,061	0,066	0,037
Child never enrolled	0,050	0,059	0,056	0,054	0,167
Child attends government school	0,804	0,974	0,969	0,970	0,715
Children test scores					
Child reads words	0,698	0,642	0,643	0,759	0,747
Child does basic maths	0,893	0,834	0,858	0,767	0,766
Child reads words and does basic maths	0,682	0,628	0,634	0,704	0,694
Chid passes math test	0,364	0,487	0,538	0,389	0,361
Chid passes language test	0,490	0,433	0,419	0,510	0,493
Chid passes math and language test	0,196	0,202	0,217	0,229	0,194
Child has an imputed score	0,028	0,039	0,027	0,167	0,146

Figure A.1: Percentage of enrolled children by age cohort.

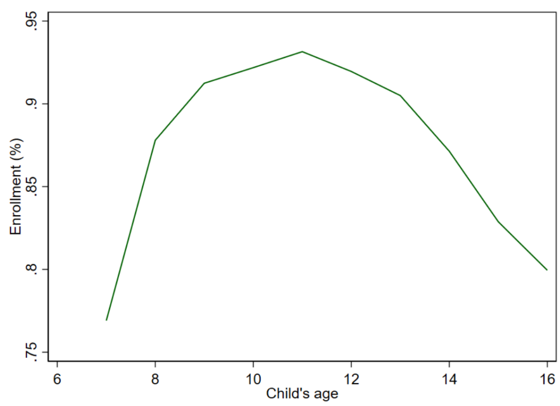
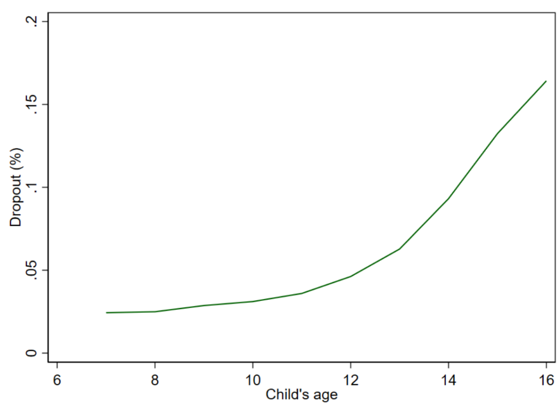
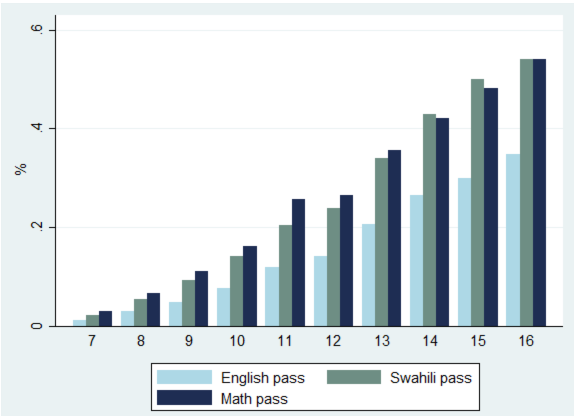


Figure A.2: Percentage of dropout children by age cohort.

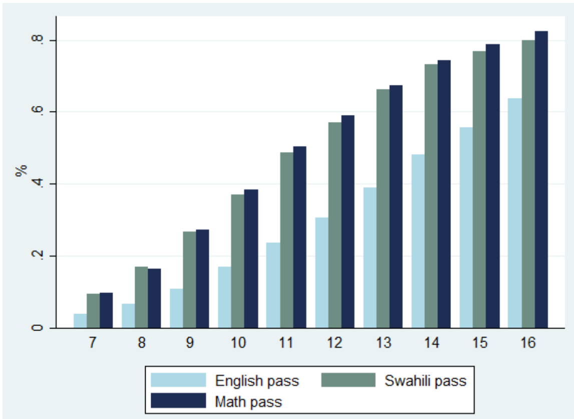


Sources: Uwezo pooled data (2010, 2011, 2012, 2013, and 2014).

Figure A.3: Percentage of children who passed the exam by age cohort.



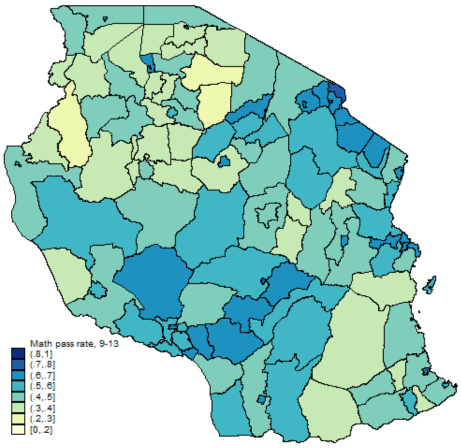
(a) Unenrolled children



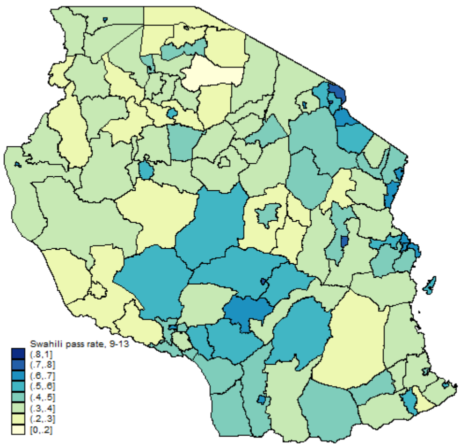
(b) Enrolled children

Sources: Uwezo data (2010, 2011, 2012, 2013, 2014).

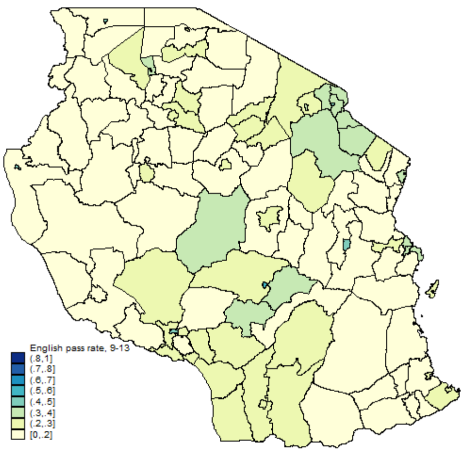
Figure A.4: Distribution of children who passed the tests



(a) Maths test, 9-13 years of age.



(b) Swahili test, 9-13 years of age.

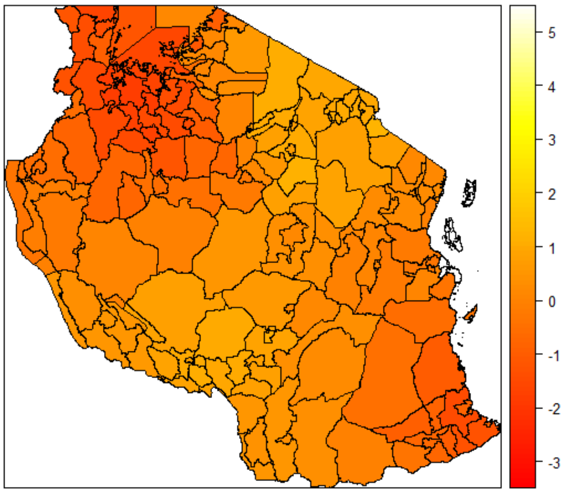


(c) English test, 9-13 years of age.

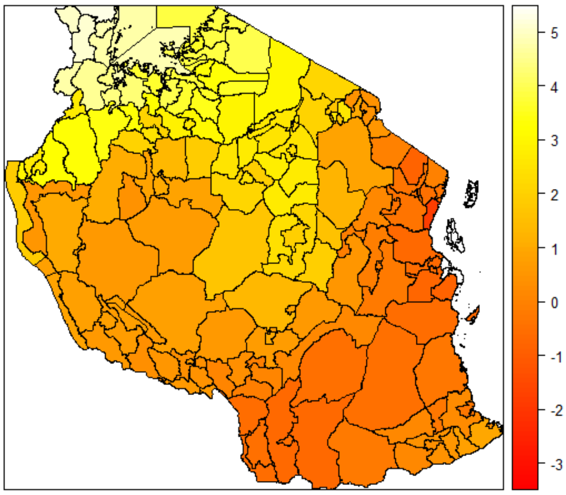
Sources: Uwezo 2011 data.

Figure A.5: Distribution of SPEI by district

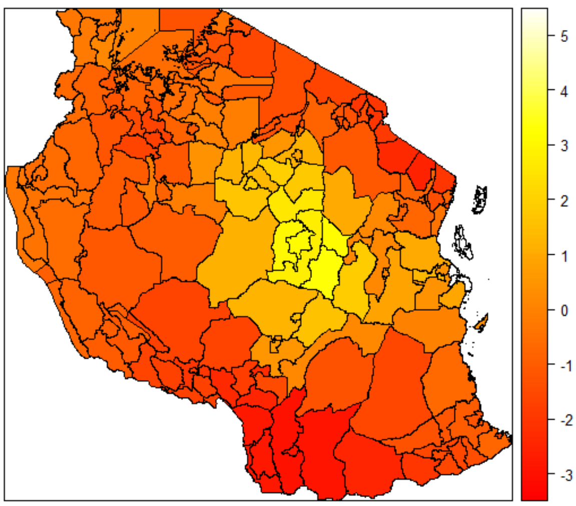
(a) In 2008



(b) In 2010

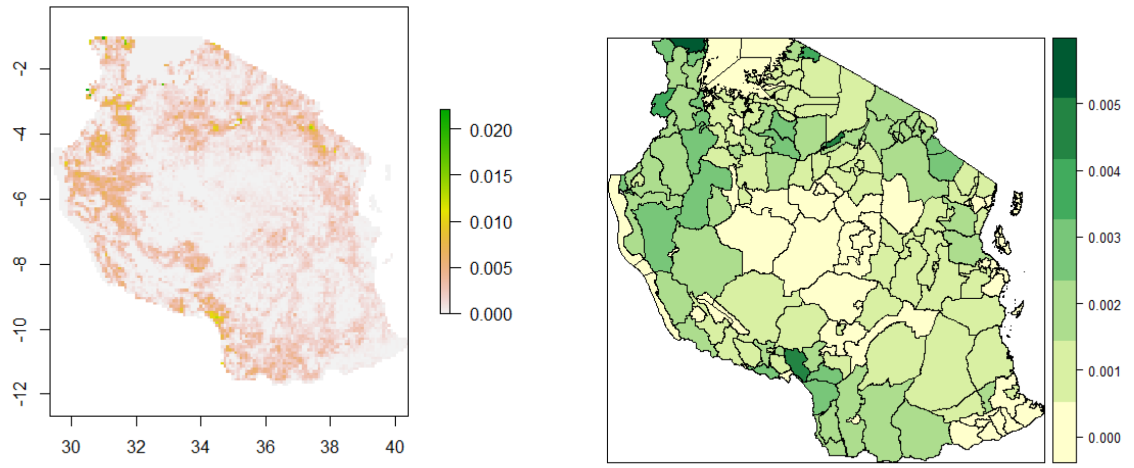


(c) In 2012



Sources: SPEI data provided by Vicente-Serrano *et al.* (2010). Note: These three maps represent the SPEI $SPEI_{j,y}$ capturing the water balance of the last 6 months. Negative values mean that climate conditions are below the historical trend.

Figure A.6: Percentage of land allocated to coffee plantation in Tanzania.

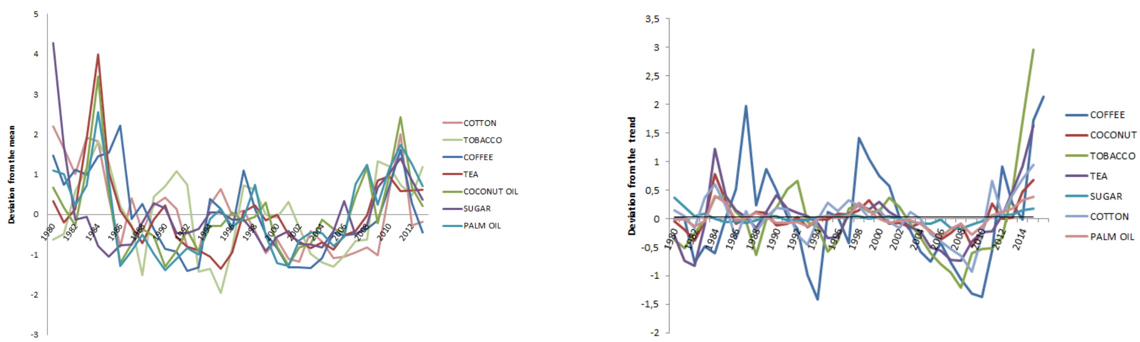


(a) Cells of 10km*10km.

(b) Average by district.

Sources: Earth Stat data (2000).

Figure A.7: Standardized price deviations for the main cash-crop commodities in Tanzania.



(a) Deviations from the mean.

(b) Deviations from the HP trend.

Sources: World Bank Commodities Price Data.

C Estimations of the mechanisms

C.1 Effect of shocks on production

Table A.3: Effects of productivity shocks on the log of Household Production.

	(1)	(2)
Positive Rainfall Shock$_{j,y-1}$	0.270	0.168
	(0.200)	(0.201)
Negative Rainfall Shock$_{j,y-1}$	-0.580***	-0.347*
	(0.222)	(0.201))
Positive Price Shock$_{j,y-1}$	-0.399	-0.019
	(0.406)	(0.380)
Negative Price Shock$_{j,y-1}$	-0.766**	-0.648*
	(0.370)	(0.348)
R-squared	0.292	
Within R-squared		0.107
Observations	7,903	7,903
Localities and Times F.E	×	×
Households F.E		×

Sources: LSMS-ISA from 2008, 2010 and 2012. Note: Production is computed in Tanzanian shillings (TZS). Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the number of days of labor in the field, and the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.4: Robustness check: Effect of various climatic variable.

Climatic variable	log(Production)			
Rainfall July-June	0.164**			
	(0.078)			
Rainfall January-December		0.230***		
		(0.087)		
Temperature	-0.037*	-0.037*		
	(0.021)	(0.021)		
SPEI-6 months March-May			0.208***	
			(0.078)	
SPEI-12 months March-May				0.146*
				(0.083)
Within R-squared	0.106	0.107	0.104	0.103
Localities and Times F.E	×	×	×	×
Households F.E	×	×	×	×
Observations	7,669	7,669	7,903	7,903

Sources: LSMS-ISA from 2008, 2010 and 2012. Note: Production is computed in Tanzanian shillings (TZS). Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the number of days of labor in the field, and the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

C.2 Effect of shocks on labor allocation decisions

Table A.5: Effect of climate and aggregate price shocks on days of child labor in the field.

	Hired labor	Adult labor	Child labor
Positive Rainfall Shock$_{t-1}$	11.32**	22.96*	31.95**
	(5.036)	(11.69)	(12.44)
Negative Rainfall Shock$_{t-1}$	1.284	-51.38**	-49.61**
	(5.177)	(21.63)	(21.58)
Positive Price Shock$_{t-1}$	0.149	-16.41	25.09
	(7.668)	(25.93)	(24.04)
Negative Price Shock$_{t-1}$	2.173	-19.45	1.088
	(4.933)	(22.95)	(20.58)
Within R-squared	0.053	0.063	0.062
Observations	3,369	7,418	5,257
Localities and Time F.E	×	×	×
Household F.E	×	×	×

Sources: LSMS-ISA from 2008, 2010 and 2012. Notes: Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, cultivated lands, the number of adults and the number of children in the household and the age of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

D Hetereogeneous effects

Table A.6: Effect of positive and negative shocks on children's activities according to household consumption

	Dropout	Grade	Dropout	Grade
	Below the median consumption		Above the median consumption	
Positive Rainfall in y-1	-0.0070	-0.0087	-0.0023	-0.0077
	(0.0057)	(0.0379)	(0.0050)	(0.0343)
Negative Rainfall in y-1	0.0045	0.0234	0.0007	-0.0241
	(0.0050)	(0.0264)	(0.0034)	(0.0207)
Positive Price in y-1	0.0044	-0.0292	0.0069	-0.0238
	(0.0066)	(0.0450)	(0.0064)	(0.0444)
Negative Price in y-1	0.0131*	-0.0283	0.0193**	-0.0198
	(0.0078)	(0.0350)	(0.0079)	(0.0465)
R-squared	0.0429	0.6790	0.0375	0.6890
Observations	183,632	157,683	143,034	129,617
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.7: Effect of positive and negative shocks on children's grades depending on the household consumption

	swahili	maths	swahili	maths
	Below the median consumption		Above the median consumption	
Positive Rainfall in y-1	-0.0803***	-0.1393***	-0.0349	-0.0748***
	(0.0279)	(0.0420)	(0.0258)	(0.0278)
Negative Rainfall in y-1	0.0522*	0.0042	0.0554*	0.0005
	(0.0313)	(0.0346)	(0.0314)	(0.0296)
Positive Price in y-1	-0.0411	-0.1035*	-0.0529	-0.0953*
	(0.0501)	(0.0544)	(0.0558)	(0.0534)
Negative Price in y-1	0.0184	0.0324	0.0451	-0.0043
	(0.0456)	(0.0572)	(0.0579)	(0.0524)
R-squared	0.3564	0.3259	0.3413	0.3143
Observations	183,632	183,632	143,034	143,034
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.8: Effect of positive and negative shocks on children's activities by gender.

	Dropout	Grade	Dropout	Grade
	Boys		Girls	
Positive Rainfall in y-1	-0.0054	-0.0060	-0.0049	-0.0089
	(0.0056)	(0.0399)	(0.0053)	(0.0327)
Negative Rainfall in y-1	0.0016	0.0116	0.0033	-0.0100
	(0.0044)	(0.0237)	(0.0038)	(0.0218)
Positive Price in y-1	0.0072	-0.0475	0.0057	-0.0076
	(0.0068)	(0.0471)	(0.0054)	(0.0356)
Negative Price in y-1	0.0168**	-0.0317	0.0140*	-0.0260
	(0.0078)	(0.0394)	(0.0075)	(0.0322)
R-squared	0.0407	0.6790	0.0400	0.6895
Observations	163,263	142,315	163,403	144,985
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.9: Effect of positive and negative shocks on children's grades by gender

	swahili	maths	swahili	maths
	Boys		Girls	
Positive Rainfall Shock$_{j,y-1}$	-0.0700***	-0.107***	-0.0733**	-0.110***
	(0.0264)	(0.0315)	(0.0292)	(0.0343)
Negative Rainfall Shock$_{j,y-1}$	0.0621**	0.00427	0.0483*	0.00131
	(0.0312)	(0.0315)	(0.0278)	(0.0241)
Positive Price Shock$_{j,y-1}$	-0.139**	-0.171**	-0.119**	-0.126*
	(0.0572)	(0.0744)	(0.0521)	(0.0639)
Negative Price Shock$_{j,y-1}$	0.00720	0.0339	0.0267	0.0688
	(0.0774)	(0.0868)	(0.0841)	(0.112)
R-squared	0.365	0.333	0.363	0.327
Observations	163,403	163,403	143,343	143,343
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.10: Effect of positive and negative shocks on children's activities across age-group.

	Dropout	Grade	Dropout	Grade
	7-13 age group		14-16 age group	
Positive Rainfall in y-1	-0.0035	-0.0010	-0.0056	-0.0545
	(0.0040)	(0.0259)	(0.0132)	(0.0919)
Negative Rainfall in y-1	0.0007	0.0110	0.0124	-0.0352
	(0.0031)	(0.0197)	(0.0098)	(0.0579)
Positive Price in y-1	0.0027	-0.0183	0.0215	-0.0035
	(0.0044)	(0.0318)	(0.0155)	(0.1129)
Negative Price in y-1	0.0133**	-0.0231	0.0310*	-0.0419
	(0.0060)	(0.0278)	(0.0165)	(0.0952)
R-squared	0.0152	0.6380	0.0426	0.0963
Observations	247,416	221,037	47,742	38,847
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.11: Effect of positive and negative shocks on children's grades across age-group.

	swahili	maths	swahili	maths
	7-13 age group		14-16 age group	
Positive Rainfall in y-1	-0.0586**	-0.1232***	-0.0674**	-0.0974***
	(0.0241)	(0.0383)	(0.0310)	(0.0295)
Negative Rainfall in y-1	0.0612*	0.0025	0.0371	-0.0032
	(0.0309)	(0.0320)	(0.0369)	(0.0354)
Positive Price in y-1	-0.0382	-0.1019**	-0.0704	-0.1012
	(0.0480)	(0.0509)	(0.0702)	(0.0700)
Negative Price in y-1	0.0316	0.0184	0.0108	-0.0126
	(0.0445)	(0.0531)	(0.0719)	(0.0706)
R-squared	0.3307	0.3053	0.1243	0.0940
Observations	247,416	247,416	47,742	47,742
District F.E	×	×	×	×
Year F.E	×	×	×	×

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of land allocated to crop production by district,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child,, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.12: Effect of shocks during schooling on Test Scores depending on position in the sibling

	Swahili	Maths	Swahili	Maths
Positive Rainfall in y-1	-0.0725**	-0.1311***	-0.0796***	-0.1318***
	(0.0293)	(0.0395)	(0.0274)	(0.0389)
Positive Rainfall in y-1*eldest	0.0329	0.0803**	0.0644**	0.1104***
	(0.0333)	(0.0341)	(0.0303)	(0.0307)
Negative Rainfall in y-1	0.0591*	0.0103	0.0383	-0.0001
	(0.0354)	(0.0350)	(0.0306)	(0.0262)
Negative Rainfall in y-1*eldest	-0.0194	-0.0415	0.0005	-0.0285
	(0.0294)	(0.0294)	(0.0299)	(0.0286)
Positive Price in y-1	-0.0447	-0.1101*	-0.0012	-0.0586
	(0.0588)	(0.0583)	(0.0496)	(0.0442)
Positive Price in y-1*eldest	-0.0015	-0.0457	-0.0067	-0.0497
	(0.0365)	(0.0319)	(0.0348)	(0.0313)
Negative Price in y-1	0.0465	-0.0101	0.0731	0.0374
	(0.0534)	(0.0567)	(0.0469)	(0.0483)
Negative Price in y-1*eldest	0.0057	0.0348	0.0255	0.0499*
	(0.0265)	(0.0284)	(0.0265)	(0.0275)
R-squared	0.3521	0.3225	0.3513	0.3167
Observations	278,804	278,804	249,505	249,505
District F.E	×	×	×	×
Year F.E	×	×	×	×
Sample	All	All	Attend	Attend

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.13: Effect of shocks during schooling on Test Scores depending on the crops'intensity

	Swahili	Maths	Swahili	Maths
Positive Rainfall in y-1	-0.0953***	-0.0975**	-0.0979***	-0.0891**
	(0.0337)	(0.0439)	(0.0334)	(0.0441)
Positive Rainfall in y-*crop land	0.0391*	-0.0177	0.0436*	-0.0185
	(0.0230)	(0.0305)	(0.0223)	(0.0282)
Negative Rainfall in y-1	0.0876**	0.0476	0.0706**	0.0392
	(0.0392)	(0.0407)	(0.0327)	(0.0303)
Negative Rainfall in y-1 *crop land	-0.0431*	-0.0574**	-0.0394**	-0.0508**
	(0.0236)	(0.0242)	(0.0195)	(0.0201)
Positive Price in y-1	-0.0532	-0.1279**	-0.0068	-0.0743
	(0.0608)	(0.0594)	(0.0534)	(0.0457)
Positive Price in y-1*crop land	0.0063	0.0215	-0.0112	0.0064
	(0.0345)	(0.0351)	(0.0326)	(0.0289)
Negative Price in y-1	0.0567	0.0144	0.1019*	0.0760
	(0.0618)	(0.0633)	(0.0556)	(0.0530)
Negative Price in y-1*crop land	-0.0403	-0.0224	-0.0633	-0.0390
	(0.0429)	(0.0457)	(0.0402)	(0.0391)
R-squared	0.3576	0.3266	0.3570	0.3207
Observations	326,666	326,666	292,343	292,343
District F.E	×	×	×	×
Year F.E	×	×	×	×
Sample	All	All	Attend	Attend

Sources: Uwezo data from 2010 to 2014. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are years dummies, the percentage of lands allocated to crop production by district ,the number of adults and the number of children in the household, age dummies, the gender and the birth order of the child, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

E Robustness checks

Table A.14: Effect of continuous climate and price variables on sample selection (beta coefficients).

	Mortality	Migration
Positive Rainfall in y-1	-0.005	-0.006
	(0.006)	(0.005)
Negative Rainfall in y-1	0.009	-0.008
	(0.007)	(0.005)
Positive Price in y-1	0.004	-0.003
	(0.017)	(0.013)
Negative Price in y-1	0.006	-0.006
	(0.016)	(0.011)
R-squared	0.007	0.012
Observations	8,525	11,719
Year F.E	×	×
District F.E	×	×
Households F.E	×	×
Sample	Agricultural HH	Children aged 7-16

Sources: LSMS-ISA from 2008, 2010 and 2012. Notes: Standard errors, clustered by district, are reported in parentheses. Controls are survey month dummies, the number of adults and the number of children in the household. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.15: Effect of climate and prices on quality of education

	(1) Teachers's absenteism	(2) Qualified teachers	(3) Access water
Positive Rainfall in month-1	-0.006	0.004	-0.004
	(0.010)	(0.028)	(0.027)
Negative Rainfall in month-1	-0.016**	-0.013	0.005
	(0.007)	(0.017)	(0.013)
Positive Price in y-1	0.001	-0.023	0.041
	(0.008)	(0.032)	(0.028)
Negative Price in y-1	.	.	.
	.	.	.
R-squared	0.04	0.006	0.02
Observations	11,732	11,732	12,060
District F.E	×	×	×
Month and Year F.E	×	×	×

Sources: Uwezo data from 2010 to 2014. Notes: Standard errors are clustered at the district level and are reported in parentheses. I control by the number of recorded actual teachers. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

Table A.16: Robustness checks: Effect of shocks on the schooling status

	Dropout	Grade	Dropout	Grade
Length positive climate shocks	-0.0023	-0.0945**	-0.0036	-0.0860*
	(0.0063)	(0.0426)	(0.0081)	(0.0473)
Length negative climate shocks	-0.0058	-0.0636*	-0.0020	-0.0418
	(0.0056)	(0.0359)	(0.0067)	(0.0411)
Length positive price shocks	0.0473	-0.5567***	0.0490	-0.6208***
	(0.0433)	(0.2129)	(0.0468)	(0.2346)
Length negative price shocks	0.0027	0.0281	0.0092	0.0069
	(0.0032)	(0.0271)	(0.0058)	(0.0343)
R-squared	0.0858	0.6888	0.0836	0.7264
Observations	7,584	7,151	7,584	7,151
District F.E	×	×	×	×
Year F.E	×	×	×	×
Household F.E			×	×

Sources: LSMS data from 2008 to 2012. Note: Standard errors are clustered at the district level and are reported in parentheses. Controls are the number of adults and the number of children in the household, age dummies, the age and the education of the household head. ***,**,* mean respectively that the coefficients are significantly different from 0 at the level of 1%, 5% and 10%.

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