Shocks and child labor: the role of markets

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Abstract

Economic shocks have been shown to affect child labor and particularly so when households fail to access credit. This paper endeavours to assess whether access to agricultural labor markets also reduce the impact of shocks on child labor. Using panel data from Tanzania, we confirm that households respond to transitory productivity shocks by changes in child labor, but that (1) child labor increases with increases in rainfall, (2) it increases less when households have access to a labor market and (3) the agricultural labor market seems more efficient than the credit market to smooth rainfall shocks. These findings are consistent with the theoretical model offered in the paper. They highlight that imperfect agricultural labor markets are important determinants of child labor.

JEL Classification: O12, O13, O15, J13, J43.

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Introduction

In Africa, 58 millions children are engaged in some economic activity.[1] Despite a steady economic growth and a clear reduction in poverty, the share of working children declines only slowly.[2] This is in stark contrast with huge improvements obtained in other dimensions of human capital, such as education and health, in the continent.[3] After 15 years of intensive research on child labor, this phenomenon is now largely perceived as negligible as long as children are enrolled in school. One reason explaining this disinterest is that the bulk of child labor is invisible since it is performed on the household farm. The available options to reduce such work are indeed limited. However, in Tanzania, our country of study, 20% of working children[4] declare that their activity prevent them from learning correctly and 20% of them have already been injured because of their activity.[5] As a consequence, working is likely detrimental to current well-being and future streams of income of the child.

There are conflicting views on the causes of child labor (see Edmonds (2008) for a literature review). In this paper, we want to assess the role of shocks, and of credit and labor market imperfections. More precisely, because rainfall shocks are exogenous events, they are at the core of our paper. We are specifically interested in understanding how households react to such shocks and how this depends on the availability of a credit and a labor market. Two crucial points need to be made upfront. First, the effect of economic shocks on child labor has already been studied and there is some evidence that when households can borrow, they tend to use less child labor to smooth consumption (Beegle et al., 2006; Alvi and Dendir, 2011). The mechanism is straightforward: a decrease in income raises incentives to work (for everybody in the household, including children) but much less if the income reduction can be spread over several time periods thanks to credit instruments. However, most of shocks faced by households are not pure income shocks but rather also have a productivity component, meaning that they also affect the household labor productivity. Figure 1, based on the Tanzania LSMS-ISA data, shows that only 25% of shocks declared by house-

[1] Estimates based on the ILO report (Diallo et al., 2013).

[2] The poverty headcount ratio went down from 60% in 2000 to 45% in 2011. The estimated share of African children aged 5-14 in employment moved from 28.8% in 2000, 26.4% in 2004, 28.4% in 2008 to 26.2% in 2012.

[3] One possible explanation for this could be that the MDg had not objective in terms of reduction of child labor. As Edmonds and Shrestha (2014) put it, "we get what we pay for" and we should expect only limited improvements by acting on child labor only through incentives to school enrollment.

[4] 5 to 15 years old.

[5] Author's own calculations based on the child module of the 2006 Tanzania Labor Force Survey.

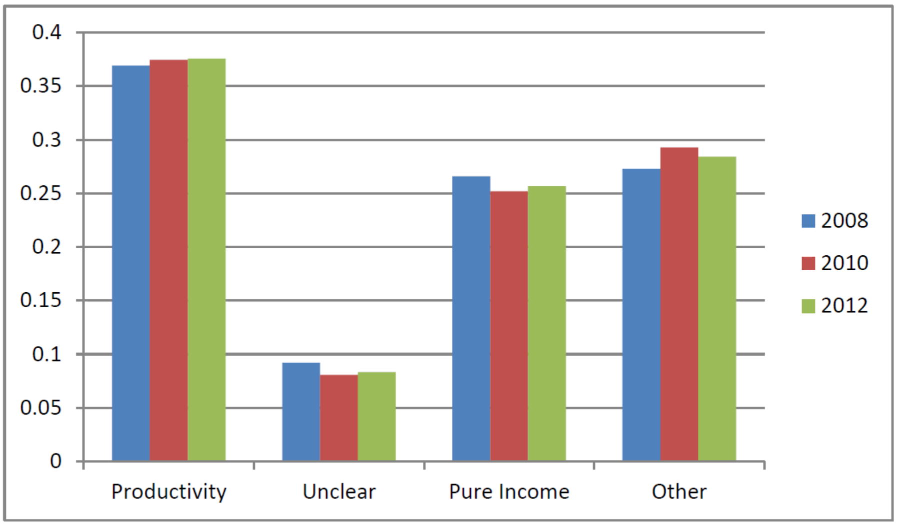
holds can be considered as pure income shocks, against at least 35% of shocks that have some productivity component. For the economic analysis, this is crucial. For instance, a *positive* rainfall shock would have two opposite effects. An income effect that leads to a decrease in child labor but also a price effect that arises form the increase in labor productivity and leads to an increase in child labor. The second point of importance is that the size of these two effects depend highly on the availability of markets. If, for instance, a labor market can provide non-household workers to a family that experiences an increase in productivity, then this household does not need to increase its own labor supply to take opportunity of the productivity increase. The size (and in the extreme, the existence) of the price effect therefore depends on the availability of a labor market. This is the non-separability result obtained in farm household models (Singh et al., 1986; de Janvry et al., 1991). As discussed before, the size of the income effect depends on the availability of credit. We first demonstrate this result in an agricultural household model in four different settings, depending on the availability of each of the two markets. In this framework, we highlight the following, maybe counter-intuitive result: in a situation where the price effect and the income effect have opposite signs,[6] the market that acts on the dominant effect is the one that reduces child labor volatility in response to productivity shocks. If, as we show later on, the price effect tends to dominate the income effect (due to poor access to the labor market) then child labor is pro-cyclical and only improvements in the labor market can lead to a reduction in child labor pro-cyclicity. In particular, access to credit/savings would only reinforce pro-cyclicity, not diminish it, thereby leading to more child labor.[7] Our study is therefore a study of the respective role of the two markets that exploit rainfall variation to identify these effects.

Based on the model, the total effect of rainfall deviations is theoretically unsigned. The second part of our paper consists in taking the model to the data. Using the three rounds of the Tanzania LSMS-ISA panel datasets, matched with three other datasets, we show that child labor does react pro-cyclically to rainfall deviations and that this is less the case in places with an active labor market. More precisely, we identify three categories of households: the vast majority is living in a very poor labor market and for them the price effect dominates the income effect, a second category of

[6]This is the case as soon as there is a price effect, meaning as soon as there are labor market imperfections.

[7]Parents who are able to transfer wealth to the next period have higher incentives to take full opportunity of the productivity increase and therefore use more child labor.

Figure 1: Share of shocks by nature in Tanzania



Source: LSMS-ISA, author's computation.

- Productivity shocks = droughts, floods, crop loss, livestock loss, fall in sale prices for crops, rise in prices of ag inputs, loss of land.
- Income shocks = job loss, rise in price of food, fire, dwelling damaged, robbery.
- Unclear = hh business failure, death or chronic disease of a hh member.
- Other = severe water shortage, death of other family member, breakup of hh, hh member jailed.

households with intermediate access to the labor market and for whom the price effect compensates the income effect and a third and very thin category of households with a good access to the labor market and for whom the income effect dominates the price effect. The identification is achieved through temporal variations due to rainfall shocks and heterogenous responses by market activity. We control for villages fixed effects that could correlate with both average child labor in the community and activity in the markets. By comparison, we observe little heterogeneity of behavior by access to the credit market. Because this is at odds with the limited evidence on this question, we provide a series of tests to understand why the credit market does not help coping with shocks. We find that households seem to have great difficulty using formal credit to smooth income even in places where banks are available. When they do so, it allows them to cope with negative rainfall shocks and avoid migration that would be harmful for the children. Apart from these extreme situations, the credit market, be it formal or informal, does not help reducing child labor. We also check empirically the validity of the assumptions in the model, such as the rigidity of prices and wages.

This paper contributes to two strands of literature in child labor. The first is the debate over the causes of child labor and notably the debate between the luxury axiom (Basu and Van, 1998), that postulates that child labor emanates from poverty, and the wealth paradox (Bhalotra and Heady, 2003), that suggests that, because of markets imperfections, only assets-endowed households can make their children work. Dumas (2007), as well, finds that land-rich households use more child labor but Basu et al. (2010) identify an inverted U-curve between child labor and landholdings.[8] This signals a dominating substitution effect at low levels of land ownership and a dominating income effect at higher levels of land ownership. A parallel strand of literature has tried to identify the effect of price variations on child labor. Similar mechanisms are at play: an increase in the productivity leads to both an income and a price effect. Here, the results are more mixed with some authors finding that the income effect dominates (Edmonds and Pavcnik (2006) using the rice price in Vietnam; Cogneau and Jedwab (2008) using the cocoa price in Côte d'Ivoire) while others find that the substitution effect dominates (Kruger (2007) using the coffee production in Brazil; Alessie et al. (1992) using price indexes in Côte d'Ivoire). This heterogeneity in results could very well come from different access to markets. We will deal with this heterogeneity.

The second strand of related literature is on the effect of economic shocks and on the heterogeneity in vulnerability, depending on assets ownership and credit availability. Beegle et al. (2006) find that economic shocks induce child labor but less so when households own assets. The dynamics of assets ownership though might be endogenous to child labor use. Alvi and Dendir (2011) provides evidence that more child labor is used in case of a major flood but that this is less the case when the household receives credit. However, credit take-up might be correlated with (unobserved) household characteristics. Edmonds (2006) also provides evidence that households fail to anticipate a future income stream, which indicates that households may fail to access credit. Jacoby and Skoufias (1997) show that shocks are associated to decreases in education, but the effects are small. Shah and Steinberg (2013), who use rainfall variations as shocks, show that investment in human capital is procyclical in early life (before age 3) and counter-cyclical later on.

The article is organized as follows: section 1 discusses the sources of market imperfections in rural areas of the developing countries and derives the effect of shocks depending on the existence and degree of perfection of the labor and credit markets respectively. Section 2 describes the data, section 3 presents the estimation while section

[8] Dumas (2007) uses data from Burkina Faso, Dumas (2013) data from Madagascar, Bhalotra and Heady (2003) data from Ghana and Pakistan and Basu et al. (2010) data from Northern India.

4 provides the results.

1 Theory: rainfall impact on child labor depends on market imperfections.

In this section, we show that rainfall variations affect child labor differently depending on the availability of credit and labor markets. We will neglect the insurance and land markets for the following reasons. First, African land markets are highly imperfect: traditional land rights often prevent households from renting out or selling their land. In our data, the share of land that is rented in is 4%. 95% of households rent in less than 37% of the land they use. [9] As a consequence, we will consider that the land market is missing and that land is given for a household. Second, insurance markets are also highly imperfect, with very little possibility to engage in a formal insurance scheme for an agricultural household. Some rainfall-based insurances have been implemented in various countries but with limited success: most households choose not to participate. It would also be very difficult to separate the effect of credit markets from insurance markets in consumption smoothing.

The theoretical section is organized as following: we start with a characterization of the rainfall effect depending on the labor market imperfections and then proceed to the credit market imperfections in case of missing labor markets. In each case, we start by describing the polar cases of perfect market and of missing market, before turning to the case of imperfect market. We eventually summarize the results in an empirical specification taking into account both types of imperfections.

1.1 The labor market

1.1.1 Labor market imperfections

Sources of market imperfections Ray (1998) provides an excellent presentation of the various market imperfections in developing countries. Information assymetries and lack of enforcement limit the possibilities of mutually advantageous exchanges on the labor market. In particular, agricultural output variation due to weather shocks or pests makes it difficult for the landlord to uncover his tenant's effort and this results

[9] In addition, studying land markets jointly with labor markets raises an identification question: perfect land and labor markets could, in theory, be substitutes for each other. Indeed, if a household had excess land, it could hire some worker to farm the land rather than sell it if the labor market is perfect, or sell the land rather than hire if the land market was perfect.

in higher supervision costs. Such costs are similar to transaction costs on the labor market and there might be a price-band (de Janvry et al., 1991), in which the landlord prefers not to hire any labor force. An additional difficulty arises from the seasonality of farm activities: all the farming households have the same tasks to undertake at the same time. This synchronicity of needs prevents the households to exchange labor and the large landowners face a labor supply shortage. Finally, the small number of actors on the market makes it difficult to guarantee that the supply meets the demand.

1.1.2 Perfect labor market: separability of decisions

We are interested in analyzing the behaviour of farm households, who have to make production and consumption decisions, as well as labor supply decisions. Agricultural households have the specificity that they take simultaneous decisions regarding their farm production and their consumption. However, it has been shown that if markets are perfect, their two decisions can be considered as "separable" from each other (de Janvry et al., 1991).[10] In order to display evidence on the role of labor market imperfections, we start by describing such a situation. We model the household as constituted of one adult and one child. We analyze the effect of rainfall on child labor with a model where the parent value the child leisure. The child may provide some on-farm labor but cannot provide off-farm work. The parent does not value his own leisure; he therefore provides one unit of labor. In a context of perfect labor markets, the parent may hire external workers or provide off-farm (wage) work. The household maximizes its utility:[11]

$$
\begin{aligned}
& & \max U(C, l_c) = \phi(C) - l_c \qquad (1) \\
s.t. & & C = AF(l_a + \delta l_c) + w(1 - l_a)
\end{aligned}
$$

where C is household consumption, l_c is child work hours, l_a is adult work hours on the farm (household and non-household labor), w is the market wage, F is a production

[10] A simple way to analyze the decision process is to consider that households start with choosing production levels and production inputs (including farm labor). This choice provides them with a given level of farm profit; then they take their consumption decisions given this profit level. In particular, they can freely chose the household leisure demand and labor supply since they can rely on the labor market to satisfy their needs on the production side. If their labor demand is greater than their labor supply, they hire; otherwise they provide some market work. This has strong consequences: no farm characteristics should affect consumption decision (including labor supply), once profit is controlled for.

[11] For the sake of simplicity, we neglect here the non-negativity constraint on l_c, this will be taken into account in the empirical part.

function (which depends on the amount of land, which is kept implicit for the sake of simplicity), δ is the labor marginal productivity ratio between adults and children, A is a productivity factor. This productivity factor will reflect rainfall deviations from the norm ion the area. The utility is assumed to be additively separable between consumption and child leisure. We assume that $\phi' > 0, \phi'' < 0, F' > 0$ and $F'' < 0$.

The model deserves some attention on the productivity term. In the empirical analysis, the productivity shock will be a rainfall shock. It is quite clear that most of the rainfall variation is common to households from the same area. A variation in rainfall could be associated with variations in crop prices and wages. However, labor market rigidities will limit the macro-effect of rainfall.[12] The lag between the period where labor has to be supplied and the period in which prices vary will also reduce the possible macro-effect of rainfall on food prices at the time of the decision. We estimate changes in prices associated to rainfall deviations from the norm. The prices that are used are for the most important crops in Tanzania as well as the most exchanged commodities throughout the country. We show in Table 1 that prices are quite inelastic. In particular, we only find that one positive standard deviation in rainfall from the norm decreases the rice price by 4%. The other coefficients are non significantly different from 0 at the 10% level. With regards to wages, they seem to be elastic to negative deviations but not to positive deviations and more for wages in agricultural activities. However, the coefficient, while large, is very imprecisely estimated and is not significant anymore at the 10% level if we drop the village fixed effects. As a consequence, we simplify the theoretical model by only taking into account a household-level effect of rainfall on labor supply decisions.

[12]Evidence on India are inconclusive: Jayachandran (2006) finds that wages adjust to productivity shocks while Kaur (2014)find wage rigidity.

Table 1: Prices on rainfall

Panel A : Rainfall in year t, Village fixed effects								
	Rice	Maize	Casava	Sugar	Beans	Kerosene	Wage	Ag. wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Positive rainfall	-55.25*	-670.2	98.63	852.5	245.5	15,993	-1,871	-3,582
	(32.63)	(472.9)	(156.6)	(708.7)	(496.7)	(17,347)	(22,808)	(39,810)
Negative rainfall	-9.793	269.1	-89.40	233.1	-169.3	-8,586	-18,415	-52,562*
	(27.89)	(425.0)	(120.1)	(596.7)	(412.9)	(14,609)	(21,030)	(31,627)
Village fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	942	737	320	946	912	872	2003	583
R-squared	0.669	0.164	0.172	0.014	0.006	0.052	0.141	0.174
Mean of the variable	1381	899.8	548.8	1941	1479	2660	143851	113682
Panel B : Rainfall in year t, Village random effects								
	Rice	Maize	Casava	Sugar	Beans	Kerosene	Wage	Ag. wage
	(1)	(2)	(3)	(4)	(5)	(6)		
Positive rainfall	-62.10**	72.52	-20.56	591.3	72.54	-7,581	-23.88	-5,729
	(27.90)	(364.2)	(113.8)	(539.2)	(422.0)	(13,528)	(19,191)	(37,816)
Negative rainfall	-9.590	328.4	10.77	304.3	188.9	2,597	-21,886	-48,023
	(24.23)	(339.6)	(86.97)	(469.9)	(358.6)	(11,772)	(18,215)	(29,702)
Village fixed effects	no	no	no	no	no	no	no	no
Observations	942	737	320	946	912	872	2003	583
Mean of the variable	1381	899.8	548.8	1941	1479	2660	143851	113682

Note: Years of the panel included in the estimation: 2008-09, 2010-11, 2012-13. Additional control variables are for columns (1) to (6): year and unit of measure. Additional controls for columns (7) and (8): gender, age, age square, survey month, period over which the wage is declared, year. The standard errors are not clustered. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

The first-order conditions of the maximisation problem are:

$$\delta AF' = \frac{1}{\phi'} \tag{2}$$

$$AF' = w \tag{3}$$

Child labor is chosen such that its marginal cost (in foregone utility) is equated to its marginal benefit (increased utility from additional consumption), while household adult work is chosen such that its marginal productivity in the 2 activities are equal. No constraint prevails on the amount of labor that can be hired or sold on the market. In apendix 5.1.1, we show that an increase A leads to a reduction in child labor, due to a pure income effect:

$$\frac{\partial l_c}{\partial A} = -\frac{F}{\delta AF'} < 0 \tag{4}$$

However, the assumptions here are stringent: external labor has to be a perfect substitute for household labor. This is unlikely to be the case. We now depart from this assumption by assessing the rainfall effect on child labor in the absence of an adult labor market.

1.1.3 Case of no labor market

With a missing labor market, the household maximizes its utility under the constraint of equating labor supply and labor demand:[13]

$$\max U(C, l_c) = \phi(C) - l_c \tag{5}$$

$$s.t. \qquad C = AF(1 + \delta l_c)$$

The first-order condition is:

$$\delta AF' = \frac{1}{\phi'} \tag{6}$$

[13] More generally, we know that its production choices depend on its characteristics (laborforce and age of the household members, for instance), while the consumption choices depend on the farm characteristics (inputs), even conditional on the profit.

We show in Appendix 5.1.2 that a change in A leads to the following variation in child labor:

$$\frac{\partial l_c}{\partial A} = -\frac{F + \frac{\delta F'}{\phi''/\phi'^2}}{\delta A F' + \delta^2 A \frac{F''}{\phi''/\phi'^2}} \tag{7}$$

The denominator is positive but the sign of the numerator is unknown. The first term of the numerator is similar to the income effect we observed in the previous case, the second is the price effect. Even though terms in the different regimes cannot be compared since the production and utility levels do not remain the same from one regime to the other, it is important to note that the first-order effect of the absence of the labor market is to add this price effect. Since the income effect and the price effect are of opposite signs, it cannot be ascertained theoretically whether the effect of rainfall shocks is larger with or without labor markets.

In this paper, we focus on rainfall variations (R) as a source of variations in income and productivity. To sum up, in case of missing labor market, child labor is determined by household income (I), child shadow wage (w^*)[14] and other characteristics (Z):

$$l_c = l_c(\underset{-}{I}, \underset{+}{w^*}, Z).$$

More rainfall is associated to a greater available income ($I(\underset{+}{R})$) but also to a greater marginal productivity of labor ($w^*(\underset{+}{R})$).

1.1.4 Existing but imperfect labor market

Both cases are extreme, where adults can hire in/out as much as they want. A more realistic case is obviously the situation in which the labor market exists but is imperfect. This can be modeled either by adding transaction costs or by limiting the extent to which households are able to use the market. This leads to several regimes (as in Dumas (2013)) and is therefore quite difficult to identify empirically. We will take a simpler route by acknowledging that, in the imperfect case, households may have some limited ability to hire or sell laborforce. The better the market, the easier it is to hire in/out and the lower the price effect.[15] At the extreme of a perfect labor market,

[14] The sadow wage is defined by the child's labor marginal productivity at the equilibrium.

[15] Another way to present it is simply to say that the village is made of households who are constrained and households who are not constrained; the relationship that will be estimated is an average one and the more households constrained there are, the stronger the price effect of rainfall. This leads to the same conclusion.

there is no price effect anymore. By comparison, we expect the change in the income effect associated to an "improvement" in the market to be a second-order one: when offered more opportunities, the households will change their behavior and therefore may reach a higher level of income. Under the assumption that the 2nd-order effects are negligible, the price effect decreases when the labor market is improved, while the income effect remains broadly constant.

The relationship between child labor supply and rainfall variations results from an income effect and a price effect and the size of the price effect depends on the degree of perfection of the labor market.

$$l_c = l_c(I(R), w^*(R) \cdot (1 - LM), Z)$$

where LM stands for labor market and takes continuous values from 0 (no labor market) to 1 (perfect labor market).

If we linearize this relationship around R_0, the average rainfall in the village, and note $\Delta R = R - R_0$ the deviation from the average, we obtain:

$$\begin{aligned}
l_c &= l_c(I(R), w^*(R) \cdot (1 - LM), Z) \\
&= l_c(I(R_0), w^*(R_0) \cdot (1 - LM_v), Z) \\
&\quad + l_{c1} \cdot I'(R_0) \cdot \Delta R \\
&\quad + l_{c2} \cdot w^{*'}(R_0) \cdot (1 - LM_v) \cdot \Delta R \\
&\equiv K_v + \alpha_0 \Delta R + \beta_0 \Delta R \cdot (1 - LM_v) \\
&= K_v + (\underset{-}{\alpha_0} + \underset{+}{\beta_0}) \Delta R - \underset{+}{\beta_0} \Delta R \cdot LM_v
\end{aligned}$$

α_0 is the income effect of rainfall on child labor, β_0 is the price effect. $(\alpha_0 + \beta_0)$ is the effect of rainfall variations on child labor with missing labor market. It can be either positive or negative, depending on the relative size of the income (α_0) and price (β_0) effect. β_0 measures the difference in the rainfall effect when the labor market works better.

If $\alpha_0 + \beta_0$ is positive, then child labor is procyclical with rainfall when the labor market is missing (positive covariance of child labor with rainfall). An improvement in the labor market should be associated to a lower pro-cyclicity of child labor with rainfall. When $LM = 1 + \frac{\alpha_0}{\beta_0}$, rainfall deviations have no effect anymore on child labor since the price effect offsets exactly the income effect. With further improvements in the labor market above this level, child labor starts being counter-cyclical. If, on the contrary, $\alpha_0 + \beta_0$ is negative then child labor is counter-cyclical even with a missing labor market and improvements of the labor market leads to a worsening of the relationship between child labor and rainfall.

1.2 Adding a credit market

We now turn to the analysis of the credit market. Households are fully able to transfer wealth over periods only if they have access to a credit market. In most cases, they cannot because they are poor and lack the sufficient collateral. Because institutions are weak, repayment cannot be enforced and this limited liability leads to credit rationing (Ray, 1998; Bardhan and Udry, 1999). However, large interventions aiming to improve households' access to credit have been implemented, and it has probably improved over the last decades.

With the previous model as a basis, we analyze the effect of rainfall variations on child labor, depending on whether a credit market is available. First, our terminology of "credit" market is loose here: actually, given that we are interested in negative and positive rainfall variations, only the ability to transfer income over periods is relevant and not specifically the ability to borrow. As a consequence, "credit" here encompasses as well the ability to save. If households are able to save even when no credit market is available, then only negative shocks will have different impact depending on the availability of the credit market. We will look into that question in the empirical part.

1.2.1 Credit market (and no labor market)

In this section, we assume that the household lives for two periods and that, in the second period, it does not receive any shock. The household therefore maximizes:

$$\max U_1 + \beta U_2 = \phi(C_1) - l_{c1} + \beta\phi(C_2) - \beta l_{c2} \tag{8}$$

$$s.t. \quad C_1 = AF(1 + \delta l_{c1}) - S \tag{9}$$

$$C_2 = F(1 + \delta l_{c2}) + \frac{1}{\beta}S$$

where S denotes savings, the subscript 1 the first period, and the subscript 2 the second period. Labor markets are missing in both periods.

The first-order conditions are:

$$\begin{aligned}
\phi_1' &= \phi_2' &(10)\\
A\delta F_1' &= \frac{1}{\phi_1'} &(11)\\
\delta F_2' &= \frac{1}{\phi_2'} &(12)
\end{aligned}$$

The first one implies that, as expected, consumption should be smoothed between period 1 and period 2. We show in Appendix 5.1.3 that:

$$\frac{\partial l_{c1}}{\partial A} = -\frac{\frac{1}{1+\beta}\left(F_1 + \beta\frac{AF_1'^2}{F_2''}\right) + \frac{\delta F_1'}{\phi''/\phi'^2}}{\delta AF_1' \cdot \frac{1}{1+\beta}\left(1 + \frac{A\beta}{F_2''}\right) + \frac{\delta^2 AF_1''}{\phi''/\phi'^2}} \tag{13}$$

This has to be compared to the expression obtained in the no credit-no labor case (eq. 7). The main difference is on the income effect. Indeed, when offering the ability to smooth income between periods, only a share of the additional income is consumed and the income effect on child labor supply is lower. Conversely, if rainfall is lower than usual, ability to borrow will allow the household to smooth over periods and therefore to limit the income effect. If there was an insurance market or if the number of periods is sufficiently long, then there would be no income effect anymore. However, whether this translates into a reduction in child labor hours remains to be discussed in the case of our model.

1.2.2 Existing but imperfect credit market

Again, if we focus on the first-order effects, then the relationship between child labor and rainfall can be summarized in the following way:

$$l_c = l_c(I(R) \cdot (1 - CM), w^*(R), Z)$$

where CM stands for credit market and takes continuous values from 0 (no credit market) to 1 (perfect credit market). After linearization around R_0, we obtain:

$$\begin{aligned}
l_c &= K_v + \alpha_1 \Delta R + \beta_1(1 - CM_v)\Delta R + \beta_1 \Delta R\\
&= K_v + (\underset{-}{\alpha_1} + \underset{+}{\beta_1})\Delta R - \underset{-}{\alpha_1}\Delta R \cdot CM_v
\end{aligned}$$

where α_1 is expected to be negative. In absence of a price effect (β_1) and with a credit market, child labor is smoothed between periods. However, with missing labor market, $\alpha_1 + \beta_1$ is unsigned. If $\alpha_1 + \beta_1 > 0$ then an improvement of the credit market leads to a greater pro-cyclicity of child labor with rainfall. If, on the contrary, $\alpha_1 + \beta_1 < 0$ the credit market improvement leads first to a decrease in counter-cyclicity and then to procyclicity.

2 Data

2.1 The Tanzania LSMS-ISA dataset

We use four independent sets of data and match them. The LSMS-ISA (Integrated Survey on Agriculture) panel data are our main source of information. They were collected in Tanzania in 2008-09, 2010-11 and 2012-13.[16] Observations are clustered in 410 enumeration areas. The survey is representative of the national population and is made of 3,265 households in the first wave. The survey team managed a very low attrition rate of 4.8% over the whole course of the panel. For the purpose of this study, we are only interested in households who live in rural areas.

These data are particularly suitable for the study: very detailed information is collected both on the household side and on the farm side. Farm labor hours are collected for each household member. Farm labor is recorded over one year and this is done by asking separately time spent on land preparation and planting, weeding and harvesting. Our key variable will be the number of days of activity on the farm provided by children.[17]

2.2 Other sources of information: Labor Force Survey, Household Budget Survey and Rainfall record

The main difficulty with these data comes from the fact that only 8 households are surveyed in each village. We are reluctant to use these 8 households to build our credit and labor market measures, since this would lead to endogeneity biases. For this reason, we use another dataset to assess market depth. We also do so because

[16] More precisely, from October 2008 to September 2009, then from October 2010 to December 2011 and from October 2012 to November 2013. The data are available upon request on the website of the LSMS.

[17] Market work is also recorded for each individual older than 5, but hours of work were only recorded for the previous week. Domestic work (and hours) is only recorded for the previous day. We do not use these variables in our main analysis but they allow us to check that the assumptions of our model are valid, in particular the absence of child labor market.

our working hypothesis is that market functioning varies little from one period to the next and there is little to loose in using a constant measure of market activity.[18] We match our LSMS observations with the Tanzania Labor Force Survey (LFS) collected in 2005. In the LFS, we will proxy availability of a labor market by the activity on the market. Indeed, the higher the transaction costs, the fewer the households who want to engage in transactions. Two questions are particularly relevant: whether the household has at least one member providing wage work, and whether the household hires wage workers. We aggregate this information at the ward level.[19] If a LSMS village can be matched with its ward in the LFS, we do so. Otherwise, we match the LSMS village with its district surveyed in the LFS and use the average use of the market in the district. For each village surveyed in the LSMS, two variables are available: the share of households with at least one member providing wage work, and the share of households hiring workers. We normalize these two variables so that they range from 0 to 1[20], both for the ease of comparison and for the ease of interpretation. The first measure is then called the "Labor market (Wage)" and the second the "Labor market (employed)". When they are equal to 0, there are no transactions on the labor market, the market is missing. It is difficult to assert above which threshold the market can be considered as “perfect". Given that we have scaled the labor market measures so as to range from 0 to 1, we will state that the market is perfect when the measure equals 1. Finally, were villages closed-economies, these two measures would reflect the exact same information. In practice, their correlation only amounts to 0.30. However, given our interpretation, we expect quite similar results with these two variables. Finally, we have to mention that this procedure restricts the area under study to mainland Tanzania, since the LFS was not covering Zanzibar. As a result, we cover 227 rural localities surveyed in the LSMS.

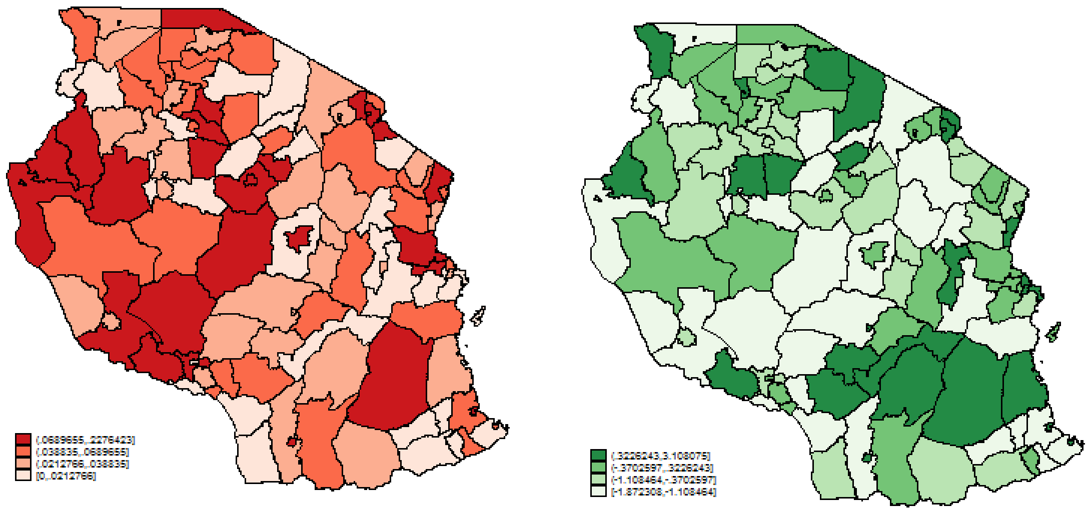
We apply a similar methodology to build our credit measure. Again, we rely on a external source of information, namely the Household Budget Survey (HBS), collected in 2006. This survey includes the following information with regards to credit: availability of a bank within 5 kilometers from the household, whether household members own a bank account, whether household members have taken a loan in the previous 12 months, and whether household members participate in an informal savings

[18]Another way to put it is to say that it would be very difficult to achieve identification of the effect of markets through time variability in these markets, especially for the labor market.

[19]A ward comprises several villages. We have on average 50 observations per ward.

[20]More precisely, we set the 5th percentile at 0 and the 95th percentile at 1, so as to avoid issues with outliers in the upper-tail of the distribution.

group. Rather than using each variable independently, we build a credit market index at the ward level through a principal components analysis (the results are displayed in Appendix, Table 7.) The information is then matched with the LSMS-ISA data at the ward level if the same two wards have been surveyed, and at the district level if not. For reasons that will become clear later on, we also use as a robustness check the information provided in the LSMS-ISA regarding the availability of a bank in 2008 in the surveyed areas. This information was collected in the village questionnaires and is not built based on household use of the bank. Figures 2 show how the labor market and credit market measures are distributed over Tanzania. We see for these figures that there is no systematic relationship between the credit and the labor market, which will allow us to identify the effect of both variables.



(a) Share of households in the district who hire workers, LFS information

(b) Credit index, HBS information

Figure 2: Labour and credit markets

Finally, the data were matched with rainfall data[21], thanks to the availability of the GPS information.[22] Tanzania has two types of agriculture: in the North-North East, there is only one cropping season, that lasts roughly from November to May; the rest of the country has two cropping seasons, the short one taking place in October-February (called *vuli*) and the long one in February-July (*masika*)). In the LSMS-ISA data, households were retrospectively interviewed about working time, inputs and production during the masika and vuli seasons separately. They are all answering

[21] `http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.FEWS/.Africa/.DAILY/.ARC2/.daily/.est_prcp/datafiles.html`

[22] The data provided by the LSMS include rainfall data, both for the survey year and for the average over the last decade. However, since they do not provide the standard deviation in rainfall, we cannot standardize the rainfall deviations, hence the need to re-match the data.

for the same masika season, but the day of interview (partly) determines which vuli season they should answer for. However, there are clearly some inconsistencies with regards to the schedule and the periods the households are supposed to answer for. In addition, it is doubtful that households are able to provide accurate information for periods that are more than one year in the past. For the sake of simplicity, we use rainfall from January to December of the year of the LSMS wave. In practice, it means that for the third wave of the panel, collected between October 2012 and December 2013, we use rain fallen in 2012. This is the variable we call "Rainfall year t". "Rainfall year t-1" is the rain fallen in 2011 for observations collected in 2012-13. We provide robustness checks with regards to alternative specifications for the rainfall variable in the Appendix. Finally, we are interested in the effect of rainfall shocks: we thus compute the deviation from the mean in the area, divided by the standard deviation in the area. Mean and standard deviations are computed using years 2001-2013. Rainfall estimates are given by squares of roughly 10km x 10km, the Tanzanian territory is covered with 10^4 such small squares and 222 of them are used in our final sample. We do not discretize this information since, according to our model, any deviation, even small, could lead to an adjustment of child labor. We show in Appendix that the use of discrete shocks does not alter the results.

2.3 Child labor in the data

Conforming to the ILO definition of child labor, we focus on children aged 5 to 15.[23] We have various sources of information in the data about child labor: whether the child has worked in the week before the survey (and how many hours), which is likely impacted by the date of the survey, hours of domestic work in the day before the survey and finally hours of agricultural work in the farm over the previous year. We will mostly focus on this last variable for two reasons: first, its collection for the whole year makes it more relevant when it comes to understanding how child labor reacts to economic shocks; second, observed shocks being rainfall variation, agricultural labor is also the one the most likely to be affected. However, it is also necessary to check whether agricultural child labor is a large share of child labor, at least in rural areas.

Among the 5 to 15 years old children who live in a rural area, 76% have not worked in the last 7 days, against 24% who had an economic activity. Only 2% of children

[23]"Child labor" is made of all working children under 12 and of children between 12 and 14 years of age who work more than 14 hours per week. In our case, we do not separate these two categories since ultimately what we explain in the number of work hours, not the status work/no work.

of this age range have provided some wage work. By comparison, 17% of 20-55 years old have provided wage work in the last week. This testifies of an absent child labor market, while adults are able, at least to some extent, to sell their labor force.

Two-thirds of children have not performed any domestic work during the day before the interview. Among those who have provided domestic work, the median duration is half an hour. As expected, girls are more likely to perform domestic chores (41% of them participate against 25% for boys) but when they do so, they do not spend more hours than boys.

Among children aged 5 to 15 and who belong to a household owning some land[24], 26% have participated to the farming. When they do so, they work on average 38 days per year and 50% of the working children work more than 23 days per year. However, there is a wide discrepancy by child age, as can be shown in Table 2.

Table 2: Days of agricultural work (on the farm), by child age

Child age	Avg # of work days	Share of working children	Avg # of work days among workers
5	0.30	1.3%	22.28
6	0.75	2.7%	27.35
7	1.39	5.3%	25.92
8	2.21	8.4%	26.10
9	5.25	19.9%	26.34
10	6.63	23.9%	27.73
11	11.66	31.1%	37.48
12	14.10	41.7%	33.76
13	20.72	50.6%	40.95
14	25.31	58.4%	43.31
15	29.86	63.2%	47.24

Finally, only 10% of the 5 to 15 years old children are not enrolled in school.

2.4 Markets in the data

We use the Labor Force Survey to describe the labor market. For villages surveyed in the LSMS, the share of households who provides wage work is on average 18% and ranges from 0 to 69%. The share of households who hire in is as low as 5% on average but ranges from 0 to 48%. At this stage, we cannot rule out that (some) households choose to remain in autarky and that this stylized fact of a very low use of the labor market is the result of a choice rather than of a constraint. Indeed, small transaction

[24]Given that we restricted the sample to the rural areas of Tanzania, 93% of households do own some land.

costs can explain the low market activity if the household labor demand is close to their supply. However, if we do find that rainfall has price effects on child labor, it is symptomatic of labor market imperfections.

We use the information displayed in the Household Budget Survey to describe the credit market. For villages that are matched to the LSMS-ISA data, we find that 37% of them are less than 5kms away from a bank, that on average 14% of households have a bank account but only 3% have a credit from the bank. This last variable ranges from 0 to 26%. Finally, 8.5% of households participate in an informal savings group and this ranges across villages from 0 to 41%. The formal credit market seems therefore very much limited but households may manage to borrow from their peers.

3 Estimation

The theoretical section derives the empirical model. If we take into account the fact that observed child labor is non negative, the model is the following one:

$$\begin{aligned} l^*_{cvt} = &\quad \gamma_0 \Delta R_{vt} + \gamma_1 \Delta R_{vt} \cdot LM_v + \gamma_2 \Delta R_{vt} \cdot CM_v + X_{cvt}\beta + \xi_v + \eta_t + \epsilon_{cvt} \qquad (14) \\ l_{cvt} = &\quad \begin{cases} l^*_{cvt} & \text{if } l^*_{cvt} \geq 0 \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

where c denotes a child, living in village v at date t. The included covariates (X_{cvt}) are child's age and gender. We voluntarily restrict the number of covariates in order to reduce as much as possible the risk of endogenous variables, probably at the expense of a more precise estimation. We include year and village fixed effects. The latter controls for any fixed village characteristics. We therefore expect that level-effects of market imperfections are taken into account through these fixed effects. Obviously, varying and unobserved determinants are likely to affect child labor but unlikely to be correlated with rainfall deviations nor with any variable that would be interacted with rainfall deviations. In addition to that, our labor and credit market imperfections measures are made of observations collected in 2006/2007, before the observation of child labor in our data, and most likely in different villages. With such a specification, the risk of endogeneity is very limited. To be completely clear, let us emphasize that the source of identification of the effect of rainfall arises from the variation in child labor over time and the identification of the effect of market imperfections arises from the heterogeneity in elasticity of child labor to rainfall variation over space. Heterogeneity within areas plays no role in the identification[25] and we do not use time variation in markets to identify their effect.

An issue could come from the inclusion of village fixed effects in a nonlinear model. This "incidental parameter" problem leads, in theory, to a biased estimation. However, Greene (2004) shows, based on Monte Carlo simulations, that the bias is quite limited in a Tobit model when the number of observations by fixed effect is higher than 8. In our case, we have on average 45 observations by village (coming from three different waves and different households in each wave). However, we have a higher censoring than in Greene's simulations (75% instead of 40%). In Appendix, Table 10 provide the same regressions estimated by OLS and show that the results are similar.

Finally, because we match information from the LFS and the HBS data at the ward or district level, we cluster standard errors at the district level.

4 Results

4.1 Effect of the labor market

We first assess the effect of rainfall on child labor. Table 3, first column, shows that more rainfall in the year is associated to higher levels of child labor but the coefficient is very imprecisely estimated. We need to allow for heterogenous effect by labor market imperfection to obtain a significant effect of rainfall. In columns (2) and (3) of Table 3, we find that with missing labor market, an increase in rainfall leads to an increase in child labor. This suggests that, in such a situation, the price effect dominates the income effect. By comparison, households who have access to a labor market do not increase child labor as much. When the wage employment measure is equal to 1, the effect of rainfall turns out to be negative: only the income effect remains. This is consistent with the theoretical model. We obtain the same results with the two labor market measures. From a welfare perspective, an intermediate degree of imperfection is interesting since it allows to counterbalance income and substitution effects and therefore to smooth productivity shocks. The absence of effect of shocks on child labor is of particular interest if there is a risk of hysteresis: if children who have started working are more likely to work again.

The theoretical model suggests that positive rainfall deviations increase child labor,

[25] The same model could be estimated using areas x year as units of observations, but we would loose in precision because of our inability to control for the covariates.

the more so when adults cannot rely on a labor market to hire external workforce. Negative rainfall deviations should decrease child labor except if parents are able to work off-farm. We therefore want to check whether most of the effect is driven by positive or negative rainfall deviations. We therefore create two variables: “Positive rainfall”, which is equal to rainfall if rainfall is positive and 0 otherwise, as well as “Negative rainfall", equal to rainfall when it is negative and 0 otherwise. As a consequence, the coefficient signs for these two variables are expected to be the same as when regressing on the rainfall variable.[26] However, the coefficient size could be different, especially if households or markets are asymmetric (for instance, if households adjust child labor supply upwards but not downwards; or if markets allow adults to work off-farm but cannot hire-in). Table 3 shows that most of the action lies in positive rainfall deviations. Negative rainfall deviations do not affect child labor. This means that parents do not wish to reduce child labor when they have the opportunity to do so (lower on-farm demand) or that adults are free to provide off-farm work. By comparison, increases in rainfall lead to higher levels of child labor, that are mitigated if the labor market is better functioning. To be very clear, the labor market imperfections we are qualifying really bear on the ability to hire in; this is not about adult unemployment.

Values given in Table 3 are the marginal effects on the latent variable (l^*). Table 4 provides the marginal effect of an increase in rainfall by one standard deviation on actual days of child work (l_c) for an average child, for different values of the wage employment measure. We find that an increase in rainfall by one standard deviation increases child labor by 4.63 days for children living in a place with no labor market (panel A). This quite seemingly low value is actually an increase by a half of child work days.[27] 30.4% of the child population lives in a place with no labor market. By comparison, children living in a place with a wage employment measure equal to 0.3 (for instance) do not work more when rainfall deviates from its mean. The share of households with at least a member providing some wage work in those places is actually quite low (between 14 and 20%). This suggests that even small improvements in the prevalence of wage work could allow to smooth productivity shocks faced by households. The population can be divided into 3 groups. In the first (where the wage employment measure ranges from 0 to 0.29), children have to increase their labor supply when rainfall deviates from its mean. This first group accounts for 73% of the

[26]The negative rainfall variable takes non-positive values and an increase in negative rainfall is a lower departure from the average.

[27]In the sample, average work days is 9.9.

population. In the second (where the wage employment measure ranges from 0.30 to 0.69), children are immune from rainfall shocks. This second group accounts for 24% of the population. The third and last group is defined by a wage employment measure above 0.70 and comprises children whose labor supply vary with rainfall but the association is counter-cyclical (because of an income effect that dominates the substitution effect). This last group accounts for a small 3% of the population. There is therefore almost three quarters of the child population who would benefit from an improvement in the labor market and even small increases in the number of transactions on the labor market could achieve the goal of eliminating child labor due to productivity shocks. In addition, most of children belonging to the second group would not suffer from an increase in the labor market activity. The picture drawn by the employed workers measure is very similar to the first measure.

Table 3: Labor market: Child labor (year t) on rainfall year t

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall normalized	1.659	6.629*	4.594			
	(2.391)	(3.470)	(3.092)			
Rainfall x Labor market (wage)		-21.12***				
		(7.981)				
Rainfall x Labor market (employed)			-11.36*			
			(6.124)			
Positive rainfall				7.611	18.87***	16.12**
				(5.035)	(6.555)	(6.993)
Negative rainfall				-3.362	-4.015	-4.498
				(3.605)	(5.952)	(5.502)
Positive rainfall x Labor market (wage)					-45.46**	
					(17.90)	
Negative rainfall x Labor market (wage)					1.700	
					(18.62)	
Positive rainfall x Labor market (employed)						-31.21*
						(16.97)
Negative rainfall x Labor market (employed)						3.673
						(15.64)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,102	10,102	10,102	10,102
Pseudo-R2	0.0919	0.0921	0.0920	0.0920	0.0924	0.0922

Note: Estimation performed by maximum likelihood (tobit) on the population of children aged 5 to 15 living in rural areas. Years of the panel included: 2008-09, 2010-11, 2012-13. The variable "Labor market (wage)" is a variable comprised between 0 and 1 reflecting the share of households with a wage worker in the area. The variable "Labor market (employed)" is a variable comprised between 0 and 1 reflecting the share of households hiring workers in the area. Standard errors are clustered at the district level. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 4: Labor market: Marginal effect of rainfall (year t) on actual days of child work

Panel A: Wage employment measure	Share of hhs	Level of wage employment	Rainfall (col 2)	Positive rainfall (col 4)	Negative rainfall (col 4)
0	30.4%	3%	1.58**	4.63***	-0.95
0.1	24.9%	9%	1.08	3.46***	-0.91
0.2	17.4%	14%	0.58	2.33**	-0.86
0.3	9.3%	20%	0.07	1.22	-0.82
0.4	4.9%	25%	-0.44	0.15	-0.78
0.5	5.7%	31%	-0.97	-0.88	-0.74
0.6	4.2%	38%	-1.50*	-1.89	-0.70
0.7	0.8%	42%	-2.05**	-2.87	-0.66
0.8	0.5%	48%	-2.60**	-3.83*	-0.62
0.9	1.4%	54%	-3.16**	-4.77*	-0.58

Panel B: Employed workers measure	Share of hhs	Level of employed workers	Rainfall (col 3)	Positive rainfall (col 5)	Negative rainfall (col 5)
0	33.0%	0%	1.10	3.93**	-1.07
0.1	19.3%	3%	0.83	3.13**	-0.98
0.2	11.9%	4%	0.56	2.36**	-0.89
0.3	16.1%	6%	0.28	1.59	-0.80
0.4	3.7%	8%	0.01	0.85	-0.71
0.5	4.9%	10%	-0.26	0.11	-0.62
0.6	1.1%	11%	-0.54	-0.59	-0.53
0.7	1.2%	13%	-0.82	-1.30	-0.45
0.8	1.7%	15%	-1.11	-1.99	-0.36
0.9	6.7%	16%	-1.40	-2.67	-0.27

Note: Marginal effect of an increase in rainfall by one standard deviation on the number of actual days of child work for an average child. Estimation based on Table 3, columns specified in parentheses. The distribution given is the share of observations between the value of the measure and the next. For instance: 30.4% of children live in a place where the wage employment measure is comprised between 0 and 0.1. Such a measure corresponds broadly to a situation where 3% of households in a village/district provide wage work. Years of the panel included: 2008-09, 2010-11, 2012-13. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

4.2 Effect of the credit market

We now turn to the credit market. Columns 2 and 5 of Table 5 show that the credit market, as measured in the HBS survey, does not make much difference on the effect of shocks. Effects are quite imprecisely estimated. Given that this is at odds with the literature and the model, we also use a contemporaneous measure of the availability of credit. Indeed, if credit markets change over time, it could be that the measure obtained from HBS is only loosely related to the credit market at the time of the survey. However, we also fail to see any effect of the alternative measure (columns (3) and (6) of Table 5). This result suggests that households who live in areas with a credit market are not better able to smooth child labor in case of shocks.

Despite a seemingly surprising result, this is very consistent with information obtained from households. In wave 2012, the LSMS survey asks what households have done in order to compensate for shocks. Among households who suffered from shocks: 54% did not do anything, 20% declared to have relied on own savings, 11% received unconditional help from relatives, 2.8% changed eating patterns, 1% had an adult household member started working, 1% sold livestock, and... 0.8% obtained credit.[28]

Table 6 provides a somewhat different picture, in particular when one looks at the effect of the availability of a bank in 2008. The significant, positive and non negligible effect of positive rainfall on child labor points suggests that improvement on the credit market can lead to an increase in the pro-cyclical child labor by reducing the income effect. To put it differently, if households are able to save income for the next period, they have greater incentives to put their children to work in case of good harvests than if they had to consume all the income within the period. This is predicted by the theoretical model. This is the only coefficient significant at the 5% level. However, the sign of the effect in the last column is not consistent with the theoretical model, but again this might be explained by the fact that banks actually only allow to save not to borrow. We try to provide additional evidence on this in the next section.

We acknowledge immediately the possibility that credit and labor markets are correlated and run regressions with rainfall interacted with both the labor and the credit market. In addition, we also provide linear estimations that are not prone to the incidental parameter bias. Table 10, left panel, shows the results hold when the analysis is run simultaneously for the credit and the labor markets and when we run a linear estimation. This being done, it remains to understand why the credit market has no effect on the extent of the rainfall shock. One possibility is that the effect of the credit market is only the income effect and that income effect might be small if parents have weak preferences regarding child labor. We already have some elements of information. Going back to Table 4, we could infer that -4.77 is the income effect

[28]Use of child labor to mitigate shocks was not an offered modality.

(no price effect of rainfall when the labor market is perfect), while the price effect is equal to $4.63 - (-4.77) = 9.33$. The size of the income effect seems to be half the size of the price effect. However, before concluding to that, need to assess whether a) households manage to smooth income, b) the formal credit market helps them in doing so, c) the credit market is used to buy inputs, which affect labor productivity and d) if selective attrition explains our results. The next section provides evidence on all these questions.

Table 5: Credit market: Child labor (year t) on rainfall year t

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall normalized	1.659	3.941	1.863			
	(2.391)	(3.182)	(2.739)			
Rainfall x Credit market (2006 PCA)		-8.777				
		(10.38)				
Rainfall x Credit market (2008 bank)			-0.843			
			(4.223)			
Positive rainfall				7.611	10.67*	4.567
				(5.035)	(6.320)	(5.774)
Negative rainfall				-3.362	-1.641	-0.554
				(3.605)	(5.499)	(4.382)
Positive rainfall x Credit market (2006 PCA)					-11.27	
					(23.04)	
Negative rainfall x Credit market (2006 PCA)					-6.955	
					(13.80)	
Positive rainfall x Credit market (2008 bank)						12.10
						(8.440)
Negative rainfall x Credit market (2008 bank)						-10.56
						(6.889)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,070	10,102	10,102	10,070
Pseudo-R2	0.0919	0.0920	0.0919	0.0920	0.0921	0.0921

Note: Estimation performed by maximum likelihood (tobit) on the population of children aged 5 to 15 living in rural areas. Years of the panel included: 2008-09, 2010-11, 2012-13. The variable "Credit market (2006 PCA)" is a variable comprised between 0 and 1 reflecting the depth of the credit market in the area, based on the 2006 Household Budget Survey. The variable "Credit market (2008 bank)" is a dummy variable for the existence of a bank in the neighborhood in the 2008-09 LSMS data. Standard errors are clustered at the district level. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 6: Credit market: Marginal effect of rainfall (year t) on actual days of child work

Credit measure in 2006 HBS	Share of hhs	Rainfall (col 3)	Positive rainfall (col 5)	Negative rainfall (col 5)
0	42.9%	0.95	2.55*	-0.38
0.1	13.3%	0.74	2.28*	-0.55
0.2	12.2%	0.52	2.00*	-0.71
0.3	9.9%	0.31	1.73	-0.88
0.4	6.0%	0.10	1.45	-1.05
0.5	3.9%	-0.10	1.18	-1.22
0.6	5.6%	-0.32	0.91	-1.39
0.7	1.1%	-0.54	0.65	-1.57
0.8	1.6%	-0.75	0.38	-1.75
0.9	3.2%	-0.97	0.12	-1.92
Bank available in 2008 LSMS	**Share of hhs**	**Rainfall (col 2)**	**Positive rainfall (col 4)**	**Negative rainfall (col 4)**
0	77.8%	0.45	1.07	-0.12
1	22.2%	0.24	4.08**	-2.77*

Note: Marginal effect of an increase in rainfall by one standard deviation on the number of actual days of child work for an average child. Estimation based on Table 5, columns specified in parentheses. The distribution given is the share of observations between the value of the measure and the next. For instance: 42.9% of children live in a place where the credit market measure is comprised between 0 and 0.1. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

4.3 Looking for an effect of the credit market

In this section, we try to understand the absence of effect of the credit market. From here on, for the sake of simplicity, we only provide the results with the wage employment measure (for the labor market).

First, we run the same regressions using rainfall in year $t-1$. Our purpose is twofold. First, if households can transfer wealth from one period to the other, then rainfall in year $t-1$ can still have some effect on labor in year t. The expected effects are the following: an increase in rainfall in year $t-1$ should lead to a reduction in child labor in year t insofar as child leisure is a normal good. As a consequence, we are interested on whether rainfall in year $t-1$ has some effect, and which kind of variations (positive vs. negative) affect child labor in year t. If is only positive variations, then it means that households are able to save and therefore postpone their reduction of labor. If both positive and negative variations affect child labor then households are able to save and borrow. However, not observing a change in child labor is not a definitive test of the existence of the market since households may have very weak preferences with regards to non-child labor. In addition, there could be some hysteresis effect: children who did work in year $t-1$ are more likely to work in year t, whatever the weather conditions. Table 8 shows very little effect of rainfall in year $t-1$ on child labor in year t, despite the fact that the coefficient is positive as expected. The size of the elasticity to rainfall is of similar magnitude (and not significant) whether we consider positive or negative deviations from the norm. We also do not see any heterogenous effect by the existence of a labor market, which conforms to the intuition. Table 9 displays some marginally significant effects but that are not robust through specifications. In addition, as we will see later on, there is no significant effect of rainfall in year $t-1$ on adult farm work, while it should be the case if households had the ability to transfer wealth across periods (and value leisure). This whole set of results point to an extremely limited coverage of the credit market. However, it does not explain why we fail to detect any heterogeneity by availability of a bank.

Second, another reason why the effect of the credit market might fail to be significant is if it changes faster than the labor market. In that case, our 2006 HBS variable and, to a smaller extent, our 2008 LSMS variable might suffer from a measurement-error bias. We therefore check that the absence of effect holds when using the 2010 information on the availability of a bank, the similar 2012 information and a time-varying variable.[29] The last option is relevant if the credit market evolves quickly. However, insofar as it is not constant over time, it could correlate with other changes in the villages. The results are provided in Table 11. It shows that we do not gain any significance by using other credit variables. The evolution of the credit market does not explain its lack of effect.

Third, we directly assess whether households manage to take up loans in hardships. We therefore estimate the probability of having received some credit in the last 12 months. We use three variables in order to do so: a) any type of credit is considered, and in particular, from any source b) only formal loans are considered and c) only loans obtained from the network are considered.[30] Table 12 shows first that the results are

[29] We cannot implement a similar check by using informal credit since the only information available on this is collected at the household level. Given the small amount of surveyed households, it would be difficult to find a measure based on this information that would not be plagued by endogeneity issues.

[30] Are considered as formal loans taken from: commercial banks, micro-finance institutions, mortgage societies, insurance companies, other financial institutions. Network loans are those obtained from neigh-

consistent whatever the credit market variable. Second, it shows that households do adjust to rainfall variations with credit but that most of the action lies in the informal market: quite surprisingly, households borrow less from relatives and friends when the rainfall deviates from the norm.[31] However, because the action is in the informal sector, we fail to find any significant effect by availability of a bank. This is surprising since, among our credit market measures, the one built on 2006 HBS encompasses informal exchanges and uses actual credit, not just availability of the bank.

Fourth, in order to further check our (absence of) results on the credit market, we assess whether deviations in rainfall led to changes in other inputs than child labor, which would have affected labor productivity and hence the use of child labor. Table 16 shows that current rainfall increases adult work on the farm but not the use of pesticides nor fertilizers. More importantly, we do not see any heterogenous effect depending on the availability of the market. The absence of effect of the credit market can therefore not be attributed to changes in other inputs.

Fifth, if households are only able to obtain informal insurance from their peers, then there should be some adjustment in case of major negative shocks that the informal insurance cannot help to cope. We look at selective migration. In our dataset, there are two types of attrition: first, households are re-surveyed but have moved in another area; second, they are not resurveyed - in that case, they are also more likely to have moved. Table 13 shows that, depending on waves, between 5 and 9% of children move out of the area and/or are not resurveyed. We start by looking at whether this is related to rainfall shocks. Table 14 shows that this is the case. In particular, a negative rainfall deviation by one standard deviation ($\Delta R = -1$) decreases the likelihood of being resurveyed in the same area by 5%pt. However, there is heterogeneity by availability of the credit market: households who have access to banks manage to stay in the area. We might want to know what happens to these children who have to leave as a consequence of the negative rainfall shock. Given that they escape our dataset, we can use instead the new individuals in the households.[32] However, questions about migration are only asked to individuals older than 12. Table 13 shows that the number of additional children (aged 12 to 15) roughly matches the number of losses. A rapid

bours, friends, religious institutions and self-help groups. For the sake of clarity, other loans, such as those obtained from a money lender or from the employer are left out of these last 2 categories but are counted in the variable "has a loan".

[31] Recall that the negative rainfall variable takes negative values. Results change when one uses only discrete shocks rather than continuous deviations. This should therefore not be interpreted as the effect of a shock.

[32] Obviously, in order to do this, we use the whole sample, including urban areas.

check confirms that these children are worse-off than the others, in terms of labour supply. However, what is of interest to us is whether they are worse-off than their rural counterparts. We therefore build up a sample made of our sample children plus the additional children who have migrated. For consistency purposes, we restrict ourselves to children aged 12 to 15 years old. Table 15 shows that children who have migrated are more likely to declare as main occupation: employed (+6%pt), unpaid family worker (+6%pt) and paid family worker (+2.6%pt). They are also vastly less likely to be enrolled in school (-24%pt). Unsurprisingly, they are not more likely to be farm worker. We also look at work hours. On average, they provided 7.5 more hours of paid work in the last week, but do not seem to be providing more unpaid hours. They also provide on average 15 days less of farm labor. Based on these comparisons, it is difficult to be definite on whether they are worse-off than their rural counterparts since their increase in paid work is compensated by a decrease in farm work. However, they are clearly children more at risk of falling into more dangerous types of activities. In addition, these children only account for 4.5% of the total sample and including them in the estimation[33] could not change vastly the results.

To summarize our findings on the credit market: households seem to have great difficulty using formal credit to smooth income even in places where banks are available. When they do so, it allows them to cope with negative rainfall shocks and avoid migration that would be harmful for the children. Apart from these extreme situations, the credit market, be it formal or informal, does not help reducing child labor (because in our setting, the price effect overcomes the income effect).

Finally, even if child labor is the main topic of this paper, we might also be interested in knowing whether households manage to smooth consumption in case of shocks. We cannot look at the effects on consumption because there is a wide lag between the harvest period and the time at which the consumption is measured. Indeed, we see from the data that the consumption measured in the survey does not depend on rainfall. However, we can check if assets have been depleted or increased. We consider two categories of assets: durables that are valued as consumption goods and productive assets. Based on a long list of questions on assets ownership, we build two indices based on a principal component analysis. Table 16 shows no evidence of assets adjustments with rainfall deviations, and no heterogenous effect by existence of markets. However, it is noticeable that almost all coefficients are larger in the first

[33] We cannot do so because our estimation relies on village fixed effects and we do not know where these children have migrated from.

part of the Table (Rainfall in year t) than in the second (Rainfall in year $t-1$). It may be the case that there are changes but they are too imprecisely estimated to be detected.

4.4 Robustness checks

We also provide complementary results in order to check the validity of our estimation.

First, our theoretical (and empirical) model rules out any general equilibrium effect at the village level. We already showed that wages and prices are rigid and do not vary much with rainfall deviations. However, for our setting to be valid, we need the prices and wages to be rigid whether there is a labor (credit) market or not. In case the market for goods is better integrated in places where the labor market has less imperfections, then we could see that prices adapt to shocks in these areas, at the expense of the validity of our strategy. Table 17 shows that there is no heterogenous effect by labor market nor credit market of rainfall on main crop prices and (agricultural) wages.As a consequence, wages seem quite rigid, which of course is one mechanism driving labor market imperfections.

Second, we check whether our results are sensitive to the choice of rainfall period. We do this with two different tests. The first one consists in using only information regarding the long rainy season, since all households are interviewed on the same long rainy season (while, depending on the survey date, they are interviewed on different short rainy seasons). Recall, however, that the long rainy season does not cover the same months depending on the place of residence. Defining the rainfall period therefore is not straightforward. Table 18 provides the results when using only rainfall and child work during the last rainy season. The results are less clear than previously but go in the same direction. In addition to that check, we also run the same regressions using alternative 12-months rainfall periods (for instance, from February 1st year $t-1$ to January 30th, year t.) The whole set of results is available upon request to the author. Regressions with cut-offs around January are the ones which display larger and more precise coefficients on rainfall. We interpret this as the fact that this is the relevant period of rainfall. For comparison, we display in column (2) of Table 18 the results for period from June, 1st to May, 31st of the following year.

Third, we also check whether the results hold when one uses discrete rainfall shock variables. We define as positive shocks events where rainfall is greater than usual by more than one standard deviation, and negative shocks as events where rainfall is lower than usual by more than one standard deviation.[34] Results are provided in Table 19. We use both a Tobit estimation and a linear regression because the variability in RHS variables has been greatly reduced. The results are mostly similar to what was found before. However, column (2) finds that when the credit market is better, households exploit the opportunity by making children work more in case of positive shocks. The effect is not symmetrical for negative shocks and does not hold with the Tobit specification though. Results are not perfectly aligned in columns (3) and (4) depending on the specification.[35]

Finally, we also wish to provide evidence that imperfect labor markets are associated to more child labor (independently from rainfall). In order to do this, we have to abandon village fixed effects.[36] As already stated, labor markets functioning is likely correlated with (un)observed characteristics of the area, that may also affect child labor decisions. The results provided in Table 20 can therefore not be interpreted as causal effects of labor and credit market imperfections. However, they are clearly indicative of a strong relationship between child labor and market imperfections. The association is stronger with labor market imperfections than with credit market imperfections, which is in line with the results obtained in this paper.

Conclusion

For understanding child labor, the role of the labor market deserves as much attention as the credit market. Indeed, we find that positive rainfall shocks increase child labor supply when there is no labor market but this effect can be entirely smoothed when the labor market has a better functioning. Interestingly, a very efficient labor market fails to smooth rainfall variations since there is no price effect to counterbalance the income effect. However, only a small share of the population live in places with highly intense labor markets.

By comparison, the formal credit does not manage to smooth child labor over periods. This is in line with the theoretical model with missing labor market and in our data, this could be driven by weak preferences regarding child labor. This

[34] This amounts to discretizing our normalized rainfall at -1 and +1.

[35] Interpretation of column (3) could lead to two mechanisms: either a positive rainfall shock has long-lasting effects on the productivity (this would explain both significant coefficients) or households manage to save from one period to the next (but this would only explain the coefficient on the interaction term). Given that only the interaction term is (marginally) significant in column (4), it is difficult to choose the mechanism at stake.

[36] We allow for regional fixed effects.

suggests that much more economic policy could be devoted to improving labor markets and further research should be undertaken to understand the heterogeneity in labor market imperfections.

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5 Appendix

5.1 Proofs

5.1.1 Perfect labor market, no credit market

The first-order conditions (2) and (3) imply $\frac{1}{\phi'} = \delta w$. In this model, an increase in A does not lead to a change in C (all the increase in income is used for reduction in child labor, because of the constant marginal disutility associated to child labor). Hence:

$$\frac{\partial C}{\partial A} = F + A\left(F'\frac{\partial l_a}{\partial A} + \delta\frac{\partial l_c}{\partial A}\right) - w\frac{\partial l_a}{\partial A}$$

since $AF' = w$, we obtain:

$$\frac{\partial C}{\partial A} = 0 = F + AF'\delta\frac{\partial l_c}{\partial A}$$

and

$$\frac{\partial l_c}{\partial A} = -\frac{F}{\delta AF'} < 0$$

We can also easily show that $\frac{\partial l_a}{\partial A} > 0$.

5.1.2 Missing labor market, no credit market

We use:

$$\frac{\partial C}{\partial A} = F + \delta AF'\frac{\partial l_c}{\partial A}$$

and when deriving the first-order condition with respect to A, we obtain:

$$\begin{aligned} \delta F' + A\delta^2 F''\frac{\partial l_c}{\partial A} &= -\frac{\phi''}{\phi'^2}\frac{\partial C}{\partial A} \\ &= -\frac{\phi''}{\phi'^2}\left(F + \delta AF'\frac{\partial l_c}{\partial A}\right) \end{aligned}$$

Hence:

$$\begin{aligned} \delta A\left(\delta F'' + \frac{\phi''}{\phi'^2}F'\right)\frac{\partial l_c}{\partial A} &= -\left(\frac{\phi''}{\phi'^2}F + \delta F'\right) \\ \frac{\partial l_c}{\partial A} &= -\frac{F + \frac{\delta F'}{\phi''/\phi'^2}}{\delta AF' + \delta^2 A\frac{F''}{\phi''/\phi'^2}} \end{aligned}$$

5.1.3 Missing labor market, perfect credit market

The first-order condition (10) implies that $C_1 = C_2$. As a consequence,

$$\begin{aligned}(1+\beta)\frac{\partial C_1}{\partial A} &= \frac{\partial(C_1+\beta C_2)}{\partial A}\\ &= F_1 + \delta A F_1' \frac{\partial l_{c1}}{\partial A} + \delta\beta F_2' \frac{\partial l_{c2}}{\partial A}\\ &= F_1 + \frac{1}{\phi'}\left(\frac{\partial l_{c1}}{\partial A} + \beta\frac{\partial l_{c2}}{\partial A}\right)\end{aligned}$$

Deriving $AF_1' = F_2'$ with respect to A leads to:

$$\begin{aligned}F_1' + A\delta F_1'' \frac{\partial l_c}{\partial A} &= \delta F_2'' \frac{\partial l_{c2}}{\partial A}\\ \frac{\partial l_{c2}}{\partial A} &= \frac{1}{\delta F_2''}\left(F_1' + A\delta\frac{\partial l_{c1}}{\partial A}\right)\end{aligned}$$

and substituting in the previous equation:

$$(1+\beta)\frac{\partial C_1}{\partial A} = F_1 + \frac{1}{\phi'}\left[\frac{\beta}{\delta F_2''}F_1' + \left(1+\frac{A\beta}{F_2''}\right)\frac{\partial l_{c1}}{\partial A}\right]$$

When deriving the second first-order condition with respect to A:

$$\delta F_1' + A\delta^2 F_1'' \frac{\partial l_{c1}}{\partial A} = -\frac{\phi''}{\phi'^2}\frac{\partial C_1}{\partial A}$$

and substituting in the previous equation leads to:

$$\delta F_1' + A\delta^2 F_1'' \frac{\partial l_{c1}}{\partial A} = -\frac{\phi''}{\phi'^2}\frac{1}{1+\beta}\left[F_1 + A\delta F_1'\left(\frac{\beta}{\delta F_2''}F_1' + \left(1+\frac{A\beta}{F_2''}\right)\frac{\partial l_{c1}}{\partial A}\right)\right]$$

Hence:

$$\frac{\partial l_{c1}}{\partial A} = -\frac{\frac{1}{1+\beta}\left(F_1 + \beta\frac{AF_1'^2}{F_2''}\right) + \frac{\delta F_1'}{\phi''/\phi'^2}}{\delta A F_1' \cdot \frac{1}{1+\beta}\left(1+\frac{A\beta}{F_2''}\right) + \frac{\delta^2 A F_1''}{\phi''/\phi'^2}}$$

5.1.4 Perfect labor and credit markets

The programme writes:

$$\max U_1 + \beta U_2 = \phi(C_1) - l_{c1} + \beta\phi(C_2) - \beta l_{c2} \tag{15}$$

$$\begin{aligned}s.t. C_1 &= AF(l_a^1 + \delta l_{c1}) + w(1-l_a^1) - S\\ C_2 &= F(l_a^2 + \delta l_{c2}) + w(1-l_a^2) + \frac{1}{\beta}S\end{aligned}$$

with S savings. The first-order conditions are:

$$\phi_1' = \phi_2' \tag{16}$$

$$AF_1' = w \tag{17}$$

$$F_2' = w \tag{18}$$

$$A\delta F_1' = \frac{1}{\phi_1'} \tag{19}$$

$$\delta F_2' = \frac{1}{\phi_2'} \tag{20}$$

Eq. (16) implies that $C_1 = C_2$. Eq. (18) and (20) imply $\frac{1}{\phi'} = \delta w$ hence no change in comsumption in case of variation in A. Hence: $\frac{\partial C_1}{\partial A} = \frac{\partial C_2}{\partial A} = 0$. Since

$$\begin{aligned} \frac{\partial C_1}{\partial A} &= F + AF_1' \frac{\partial l_a^1}{\partial A} + A\delta F_1' \frac{\partial l_{c1}}{\partial A} - w \frac{\partial l_a^1}{\partial A} \\ &= F + A\delta F_1' \frac{\partial l_{c1}}{\partial A} = 0 \end{aligned}$$

thus

$$\frac{\partial l_{c1}}{\partial A} = -\frac{F}{A\delta F_1'} < 0.$$

5.2 Additional tables

Table 7: Principal component analysis in Household Budget Survey to build the credit index

Credit measure in 2006 HBS	
Variable	Credit index
Bank within 5 km distance	0.33
At least one household member has a bank account	0.46
Number of household members with a bank account	0.46
At least one household member has had a loan from a bank over the last 12 months	0.44
Number of household members with a credit from a bank over the last 12 months	0.44
At least one household member participate in an informal savings group	0.24

Table 8: Labor market: Child labor (year t) on rainfall year t-1

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall normalized	-1.068	-2.853	-2.444			
	(1.859)	(2.655)	(2.395)			
Rainfall x Labor market (wage)		9.518				
		(9.730)				
Rainfall x Labor market (employed)			5.523			
			(6.202)			
Positive rainfall				-0.785	-0.953	-1.824
				(2.728)	(4.253)	(3.766)
Negative rainfall				-1.629	-6.214	-3.675
				(4.100)	(6.241)	(5.741)
Positive rainfall x Labor market (wage)					2.380	
					(18.38)	
Negative rainfall x Labor market (wage)					20.75	
					(18.98)	
Positive rainfall x Labor market (employed)						4.539
						(9.338)
Negative rainfall x Labor market (employed)						7.458
						(15.96)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,102	10,102	10,102	10,102
Pseudo-R2	0.0919	0.0920	0.0920	0.0919	0.0920	0.0920

Note: Estimation performed by maximum likelihood (tobit). Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 9: Credit market: Child labor (year t) on rainfall year t-1

	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall normalized	-1.068	-4.244*	-1.699			
	(1.859)	(2.293)	(1.994)			
Rainfall x Credit market (2006 PCA)		14.69*				
		(7.598)				
Rainfall x Credit market (2008 bank)			3.203			
			(3.635)			
Positive rainfall				-0.785	-5.189	-2.290
				(2.728)	(3.799)	(3.006)
Negative rainfall				-1.629	-2.460	-0.425
				(4.100)	(6.173)	(4.831)
Positive rainfall x Credit market (2006 PCA)					21.17	
					(13.39)	
Negative rainfall x Credit market (2006 PCA)					3.064	
					(17.29)	
Positive rainfall x Credit market (2008 bank)						7.424
						(5.786)
Negative rainfall x Credit market (2008 bank)						-4.635
						(9.006)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,070	10,102	10,102	10,070
Pseudo-R2	0.0919	0.0920	0.0919	0.0920	0.0921	0.0921

Note: Estimation performed by maximum likelihood (tobit) on the population of children aged 5 to 15 living in rural areas. Years of the panel included: 2008-09, 2010-11, 2012-13. The variable "Credit market (2006 PCA)" is a variable comprised between 0 and 1 reflecting the depth of the credit market in the area, based on the 2006 Household Budget Survey. The variable "Credit market (2008 bank)" is a dummy variable for the existence of a bank in the neighborhood in the 2008-09 LSMS data. Standard errors are clustered at the district level. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 10: Complete and linear specifications: Child labor (year t) on rainfall year t and t-1

	Rainfall year t				Rainfall year $t-1$			
	Tobit	Linear	Linear	Linear	Tobit	Linear	Linear	Linear
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall normalized		1.438*	2.162**			-0.0760	-0.508	
		(0.746)	(1.046)			(0.545)	(0.823)	
Rainfall x Labor market (wage)			-5.898*				-2.988	
			(3.401)				(2.972)	
Rainfall x Credit market (2006 PCA)			2.777				4.659*	
			(3.100)				(2.719)	
Positive rainfall	28.61***			6.075***	6.772*			-0.511
	(5.275)			(2.261)	(3.805)			(1.114)
Negative rainfall	-9.069*			-0.997	-3.749			-0.326
	(5.503)			(1.835)	(7.763)			(1.898)
Positive rainfall x Labor market (wage)	-62.15***			-17.91***	-37.97***			-6.486
	(14.82)			(6.723)	(12.95)			(4.738)
Negative rainfall x Labor market (wage)	32.97**			5.847	38.02*			2.715
	(14.09)			(5.003)	(20.23)			(4.538)
Positive rainfall x Credit market (2006 PCA)	-6.278			8.507	8.001			6.702
	(14.21)			(6.438)	(7.876)			(4.047)
Negative rainfall x Credit market (2006 PCA)	2.163			-3.261	7.219			0.645
	(9.284)			(3.565)	(14.32)			(4.238)
Village fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,102	10,102	10,102	10,102	10,102	10,102
R-squared		0.131	0.131	0.133		0.130	0.131	0.131
Pseudo-R2	0.0718				0.0713			

Note: Estimation performed by maximum likelihood in columns (1) and (5) and by linear regressions in the others. Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 11: Other credit market variables: child labor (year t) on rainfall year t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank in	2008	2010	2012	year t	2008	2010	2012	year t	year t
Variable is	constant	constant	constant	time-varying	constant	constant	constant	time-varying	time-varying
Rainfall	1.863	1.788	2.571	2.069					
	(2.739)	(2.704)	(2.723)	(2.753)					
Rainfall x Bank	-0.843	-4.064	-5.588	-4.453					
	(4.223)	(4.305)	(4.333)	(4.203)					
Positive rainfall					4.567	9.613*	9.147	9.864*	8.568
					(5.774)	(5.780)	(5.774)	(5.769)	(5.704)
Negative rainfall					-0.554	-4.760	-3.112	-4.618	-2.979
					(4.382)	(3.942)	(4.024)	(3.826)	(4.148)
Positive rainfall x Bank					12.10	-7.672	-8.403	-12.16	-4.610
					(8.440)	(9.430)	(9.392)	(8.864)	(9.381)
Negative rainfall x Bank					-10.56	-1.098	-3.029	1.301	-7.349
					(6.889)	(8.541)	(8.284)	(6.367)	(8.167)
Bank in year t									-12.82
									(8.927)
Village fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	10,070	9,473	10,045	9,842	10,070	9,473	10,045	9,842	9,842
Pseudo-R2	0.0919	0.0922	0.0930	0.0926	0.0921	0.0924	0.0932	0.0928	0.0929

Note: Estimation performed by maximum likelihood. Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 12: Credit take up: loans in the past 12 months (year t) on rainfall year t, by availability of credit institutions

	(1)	(2)	(3)	(4)	(5)	(6)
Bank in	-	2006 (HBS)	2008	2010	2012	year *t*
Variable is	-	constant	constant	constant	constant	time-varying
Panel A: Dependent variable: Has a loan						
Positive rainfall	-0.0286*	-0.0112	-0.0344*	-0.0258	-0.0213	-0.0243
	(0.0158)	(0.0207)	(0.0177)	(0.0187)	(0.0193)	(0.0198)
Negative rainfall	0.0349**	0.0356*	0.0263	0.0329*	0.0313*	0.0277*
	(0.0140)	(0.0183)	(0.0172)	(0.0168)	(0.0165)	(0.0165)
Positive rainfall x Bank		-0.0532	0.0180	-0.0247	-0.0346	-0.0216
		(0.0642)	(0.0342)	(0.0360)	(0.0379)	(0.0387)
Negative rainfall x Bank		-0.00386	0.0303	0.0154	0.0123	0.0302
		(0.0587)	(0.0278)	(0.0310)	(0.0277)	(0.0259)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	4,022	4,022	4,007	3,772	3,988	3,922
R-squared	0.004	0.004	0.004	0.004	0.004	0.004
Panel B: Dependent variable: Has a formal loan						
Positive rainfall	0.0190*	0.0158	0.0170	0.0206*	0.0263**	0.0224*
	(0.00978)	(0.0146)	(0.0113)	(0.0121)	(0.0110)	(0.0116)
Negative rainfall	0.00713	0.0182**	0.00324	0.00634	0.00293	0.00454
	(0.00644)	(0.00823)	(0.00714)	(0.00713)	(0.00667)	(0.00673)
Positive rainfall x Bank		0.0134	0.00716	-0.0144	-0.0345	-0.0149
		(0.0359)	(0.0244)	(0.0217)	(0.0222)	(0.0178)
Negative rainfall x Bank		-0.0426	0.0138	0.00241	0.0158	0.00363
		(0.0312)	(0.0156)	(0.0180)	(0.0180)	(0.0131)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	4,022	4,022	4,007	3,772	3,988	3,922
R-squared	0.003	0.004	0.004	0.003	0.004	0.003
Panel C: Dependent variable: Has a network loan						
Positive rainfall	-0.0539***	-0.0413**	-0.0589***	-0.0541***	-0.0535***	-0.0522***
	(0.0148)	(0.0188)	(0.0162)	(0.0159)	(0.0161)	(0.0163)
Negative rainfall	0.0242**	0.0177	0.0229*	0.0265**	0.0267**	0.0211*
	(0.0106)	(0.0139)	(0.0127)	(0.0124)	(0.0123)	(0.0124)
Positive rainfall x Bank		-0.0410	0.0155	-0.0110	-0.00229	-0.0116
		(0.0556)	(0.0312)	(0.0416)	(0.0452)	(0.0407)
Negative rainfall x Bank		0.0243	0.00389	-0.00744	-0.0118	0.0142
		(0.0451)	(0.0239)	(0.0276)	(0.0259)	(0.0213)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	4,022	4,022	4,007	3,772	3,988	3,922
R-squared	0.005	0.005	0.005	0.005	0.005	0.005

Note: Estimations performed by linear regression. Years of the panel included: 2008-09, 2010-11, 2012-13. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 13: Attrition in the sample

2008-2010				
Sample in 2008:	2844			
	Attrited			Entering
Age range	5-15	12-15		12-15
Not surveyed or not in same area:	164	61	Recent migration:	60
	5.77%	6.46%		
2010-2012				
Sample in 2010:	3344			
	Attrited			Entering
	5-15	12-15		12-15
Not surveyed or not in same area:	292	91	Recent migration:	84
	8.73%	8.24%		

Table 14: Likelihood of being in the sample in the following wave

	(1)	(2)
Rainfall normalized	0.0173	
	(0.0132)	
Rainfall x Labor market (wage)	-0.0125	
	(0.0417)	
Rainfall x Credit market (2006 PCA)	-0.0543	
	(0.0334)	
Positive rainfall		-0.0552*
		(0.0322)
Negative rainfall		0.0469**
		(0.0198)
Positive rainfall x Labor market (wage)		-0.00288
		(0.0880)
Negative rainfall x Labor market (wage)		-0.00460
		(0.0668)
Positive rainfall x Credit market (2006 PCA)		0.0147
		(0.0762)
Negative rainfall x Credit market (2006 PCA)		-0.0921*
		(0.0473)
Village fixed effects	yes	yes
Observations	6,188	6,188
R-squared	0.001	0.002

Note: Estimation performed by linear regressions. Dependent variable is: whether the child is resurveyed and living in the same area in the following wave. Years of the panel included: 2008-09, 2010-11 (and 2012-13 for the outcome). Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 15: Comparison of children who have migrated and the others

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Main occupation					Hours				Days
	Ag. worker	Employed	Unpaid family	Paid family	School	Paid work (week)	Unpaid work (week)	Ag. work (week)	Dom. work (day)	Ag. work (season)
Migrated	0.0313	0.0594***	0.0581**	0.0265***	-0.241***	7.534***	1.355	-0.523	-0.0963	-14.82***
	(0.0354)	(0.00677)	(0.0238)	(0.00859)	(0.0431)	(0.876)	(0.926)	(1.326)	(0.151)	(3.959)
Male	0.0129	0.00437**	0.00854	-0.00298	-0.0274*	0.147	-1.150***	1.929***	-0.235***	0.126
	(0.0115)	(0.00221)	(0.00776)	(0.00280)	(0.0140)	(0.285)	(0.302)	(0.432)	(0.0492)	(1.290)
Age	-0.210	-0.0275	-0.349***	-0.00995	0.597***	-0.573	-0.991	-4.756	-0.445	23.60
	(0.153)	(0.0293)	(0.103)	(0.0372)	(0.187)	(3.793)	(4.011)	(5.743)	(0.654)	(17.15)
Age squared	0.01000*	0.00111	0.0133***	0.000454	-0.0251***	0.0434	0.0583	0.219	0.0167	-0.686
	(0.00568)	(0.00109)	(0.00382)	(0.00138)	(0.00692)	(0.141)	(0.149)	(0.213)	(0.0243)	(0.636)
Rural	0.150***	0.0518***	-0.0372	-0.139***	-0.0894	-6.055***	0.650	3.584**	0.194	0.762
	(0.0466)	(0.00892)	(0.0313)	(0.0113)	(0.0567)	(1.153)	(1.219)	(1.746)	(0.199)	(5.213)
Away from mother	-0.00921	0.00690**	0.0138	0.0136***	-0.0203	0.800*	-2.875***	-1.436**	-0.0775	-3.629*
	(0.0172)	(0.00330)	(0.0116)	(0.00419)	(0.0210)	(0.427)	(0.451)	(0.646)	(0.0736)	(1.929)
Away from father	0.0193	-0.00109	0.0155	0.0114***	-0.0419**	1.286***	-2.800***	-0.289	-0.0414	2.765
	(0.0161)	(0.00308)	(0.0108)	(0.00390)	(0.0196)	(0.398)	(0.421)	(0.602)	(0.0686)	(1.799)
District FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	3,558	3,558	3,558	3,558	3,558	3,558	3,558	3,558	3,558	3,558
R-squared	0.043	0.028	0.017	0.132	0.070	0.112	0.049	0.022	0.009	0.031

Note: Estimation performed by linear regressions. The sample is made of children aged 12-15 and who are in the main sample plus the children aged 12-15 who have recently migrated (less than 2 years since establishment in the new residence). Years of the panel included: 2008-09, 2010-11, 2012-13. The districts used for the fixed effects are the district of residence for non-migrating children and the district of origin for migrating children. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 16: Other outcome variables (year t) on rainfall year t and t-1

Panel A: Rainfall in year t	Adult days on the farm (1)	Fertilizers (value) (2)	Pesticide (value) (3)	Durable goods (4)	Productive assets (5)
Rainfall normalized	13.25**	3,823	-1,407	0.0552	0.0154
	(5.250)	(3,653)	(1,706)	(0.0391)	(0.0241)
Rainfall x Labor market (wage)	-8.900	-7,543	424.2	-0.145	-0.0841
	(15.49)	(9,208)	(2,046)	(0.178)	(0.0761)
Rainfall x Credit market (2006 PCA)	-14.30	-2,731	-800.9	0.0788	-0.0508
	(10.28)	(6,504)	(2,287)	(0.0993)	(0.0743)
Village fixed effects	yes	yes	yes	yes	yes
Observations	4,022	3,969	3,969	4,022	4,022
R-squared	0.002	0.004	0.001	0.157	0.121

Panel B: Rainfall in year $t-1$	Adult days on the farm (1)	Fertilizers (value) (2)	Pesticide (value) (3)	Durable goods (4)	Productive assets (5)
Rainfall normalized	-1.401	-1,983	-341.0	0.0332	-0.00364
	(5.394)	(2,785)	(1,215)	(0.0348)	(0.0186)
Rainfall x Labor market (wage)	24.52	-9,012	3,560	0.0439	0.0704
	(17.01)	(10,386)	(2,453)	(0.140)	(0.0710)
Rainfall x Credit market (2006 PCA)	-16.41	12,996	-991.4	0.0235	-0.0321
	(13.43)	(12,322)	(3,713)	(0.0903)	(0.0358)
Village fixed effects	yes	yes	yes	yes	yes
Observations	4,022	3,969	3,969	4,022	4,022
R-squared	0.002	0.005	0.001	0.158	0.120

Note: Adult work on the farm are adult household days of work + hired adults days of work. Durable goods and productive assets are indices built through principal component analysis using the number of each items owned by the household. Years of the panel included: 2008-09, 2010-11, 2012-13. Standard errors are clustered at the district level. Additional control variables are: columns (1) to (3): year; columns (4) and (5): household composition variables and year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 17: Prices and wages (year t) on rainfall year t

Rainfall in year t	Rice	Maize	Casava	Sugar	Beans	Kerosene	Wage	Ag. wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall normalized	-6.824	-199.9	105.9	-279.7	-35.44	6,165	-8,020	-59,356
	(25.36)	(290.8)	(87.22)	(341.4)	(40.33)	(6,590)	(16,851)	(39,586)
Rainfall x Labor market (wage)	-39.64	133.3	171.8	4,755	-61.93	14,938	-33,630	41,134
	(65.07)	(284.2)	(205.1)	(4,535)	(105.6)	(14,371)	(44,157)	(75,281)
Rainfall x Credit market (2006 PCA)	-32.52	-32.40	-486.2**	-2,292	208.3	-29,928	-1,462	7,297
	(58.09)	(243.4)	(195.1)	(2,169)	(193.8)	(21,704)	(33,426)	(38,602)
Village fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	942	737	320	946	912	872	2,003	583
R-squared	0.683	0.196	0.226	0.031	0.005	0.064	0.021	0.100

Note: Years of the panel included: 2008-09, 2010-11, 2012-13. Standard errors are clustered at the district level. Additional control variables are: year and unit of measure. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 18: Child labor (year t) on various rainfall year t

	Rainfall: Long Rainy Season			Rainfall from June to May		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall normalized	1.757	0.933		-1.946	0.698	
	(1.160)	(1.675)		(1.689)	(2.469)	
Rainfall x Labor market (wage)		0.844			-6.094	
		(6.502)			(9.871)	
Rainfall x Credit market (2006 PCA)		2.739			-6.467	
		(4.012)			(9.480)	
Positive rainfall			4.047			7.647*
			(2.569)			(4.324)
Negative rainfall			-2.268			-11.15*
			(2.064)			(6.533)
Positive rainfall x Labor market (wage)			-11.57			-32.52*
			(12.18)			(18.54)
Negative rainfall x Labor market (wage)			14.94			37.93*
			(9.565)			(21.51)
Positive rainfall x Credit market (2006 PCA)			4.555			6.539
			(8.852)			(19.88)
Negative rainfall x Credit market (2006 PCA)			1.258			-22.22
			(4.670)			(16.61)
Village fixed effects	yes	yes	yes	yes	yes	yes
Observations	10,102	10,102	10,102	10,102	10,102	10,102
R-squared	0.158	0.158	0.158	0.0919	0.0920	0.0924

Note: Estimation performed by maximum likelihood. Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 19: Child labor (year t) on rainfall shocks year t and t-1

	year t		year $t-1$	
	Tobit	Linear	Tobit	Linear
	(1)	(2)	(3)	(4)
Positive shock	29.63***	6.300*	10.18**	1.023
	(6.666)	(3.582)	(5.020)	(1.705)
Negative shock	5.395	-1.159	-1.504	-1.441
	(4.722)	(2.174)	(10.57)	(2.760)
Positive shock x Labor market (wage)	-87.91***	-25.32***	-64.72***	-13.09*
	(14.38)	(7.382)	(19.75)	(7.240)
Negative shock x Labor market (wage)	-24.35*	-0.743	-32.82	1.666
	(13.50)	(6.858)	(28.66)	(4.682)
Positive shock x Credit market (2006 PCA)	11.20	17.16**	16.45	6.461
	(15.81)	(6.811)	(12.29)	(5.486)
Negative shock x Credit market (2006 PCA)	4.760	-0.491	10.01	-6.064
	(10.00)	(4.417)	(20.74)	(5.746)
Observations	10,102	10,102	10,102	10,102
R-squared		0.133		0.131
Pseudo-R2	0.0703		0.0706	

Note: Estimation performed by maximum likelihood in columns (1) and (3) and by linear regressions in columns (2) and (4). Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.

Table 20: Child labor (year t) on rainfall year t: direct "effect" of markets

	Rainfall year t		
	(1)	(2)	(3)
Rainfall normalized	4.894*	3.543	5.422*
	(2.940)	(2.662)	(2.919)
Labor market (wage)	-27.13***		-23.58**
	(8.654)		(9.359)
Credit market (2006 PCA)		-14.42***	-4.870
		(5.448)	(5.596)
Rainfall x Labor market (wage)	-16.57***		-13.04
	(6.280)		(8.591)
Rainfall x Credit market (2006 PCA)		-10.98	-5.236
		(8.034)	(8.772)
Region fixed effects	yes	yes	yes
Observations	10,102	10,102	10,102
Pseudo-R2	0.0765	0.0762	0.0766

Note: Estimation performed by maximum likelihhod. Years of the panel included: 2008-09, 2010-11, 2012-13. Additional control variables are: age and gender of the child, year. ***, ** and * respectively mean that the coefficient is significantly different from 0 at the 1%, 5% and 10% level.