Child-Income as an Insurance Mechanism
Consequences for the Health-Education Relationship

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December 14, 2011

Abstract

This paper analyzes the relationships between HIV-AIDS and education taking into account the appropriative nature of child income. We first build a simple theoretical model linking parental health risk, educational choice and appropriation of future children's income. We show that considering (remittances from) child's income as an insurance asset can reverse the relationship between illness prevalence and educational investment, which may then become positive. This prediction is tested on data compiled from the DHS database for 17 SSA countries between the years 2003 to 2010 for children aged between 6 and 22 inclusive. To take into account the hierarchical nature of the data we employ a multilevel analysis. We find that in general the impact of household HIV status on educational enrollment at a point in time is negative while the effect of community HIV prevalence is insignificant. But once the data is split to account for possible differences in appropriation, the effect of community prevalence of becomes positive and sometimes significant for highly appropriable groups (rural, girls), while remaining either negative or insignificant for the rest.

Keywords: *Health risk; Education; Insurance mechanism; Remittance.*
JEL Classification Numbers: I15, I25.

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1 Introduction

This paper analyzes the link between HIV-AIDS prevalence and school enrolment. It is now well documented that health status and in particular HIV status has an important (negative) impact on child education. This is particularly true in developing countries where this negative relationship can lead to macroeconomic issues, as poverty trap. However, if we now consider the impact of health risk (which can be proxied by prevalence) rather than health status, the impact on education seems less obvious. Within risk-sharing systems, education can then act as a way to smooth consumption and to reduce the risk on wealth induced by health risk. We therefore propose here to enrich the analysis of the link between HIV and education by focusing – both theoretically and empirically – on health risk (rather than status) and on the insurance role of education.

This paper intends to interact three fields of economic literature: i) the literature about the relationship between epidemics and economic development, especially its micro-foundations aspects that study how a health shock may jeopardize a household's future capacity to save, accumulate and generate future income (Kawabata et al.[18], Wagstaff and van Doorsaler[29], Xu et al.[30] and Flores et al.[9][1]; Fortson[10] already demonstrates the impact of HIV/AIDS on children's education), ii) the literature dedicated to child labor and child income appropriation by parents, for example Basu and van Pham[1] and Schoonbroodt and Tertilt[28], iii) the literature dedicated to educational choice as old age insurance in the absence of social security, the most common situation in a lot of African countries, Ehrlich and Lui[7] for example studied the effect of changing mortality in an overlapping generations model in which children provide old-age support for their parents.

Educational choice of offsprings, as the prior fertility choice, is recognized as a means for parents to insure themselves against future income variation. Investments in children, quantitatively and qualitatively is an asset for parents, which in developing countries, is seen as a substitute to social security, see for example Nugent[23], Michel and Wigniole[22] and Ehrlich and Lui[7]. Generally this motive for having children is evident in the old-age period of parents which is often characterized by the absence of labor income and the presence of elevated health-risk. However, the fundamental nature of an insurance asset is to be mobilized differently depending on the realization of a risk: actual repayments are contingent on bad event. Starting from this point, we add to the idea of child-investment as an old-age security the notion of *changing appropriation*, giving to child-investment its very nature as a health insurance mechanism. The intensity with which parents invoke their "rights" on the income of their descendants vary depending on their health status.

[1]The welfare effects of HIV can be approximated through the share of the household budget absorbed by HIV related medical expenditures, see for example Wagstaff and van Doorslaer[29] and Xu et al.[30]. When health expenditures represent a large share of the healthcare the situation is defined as "catastrophic" as this implies either a substantial sacrifice of the household current consumption, possibly including basic needs, or the mobilization of other resources (such as savings, assets, credit and transfers from friends and family).

This is not only inspired by the necessity to draw a parallel with the classic insurance framework, but can be connected to the notion of “child income appropriation” (see Schoonbroodt and Tertilt[28]): in a lot of developing countries, the property rights on labor-income are shared between the different members of a household and, at least for a part, submitted to discretionary re-appropriation decisions coming from the household community. Bazen and Salmon[2] and McIntyre et al.[21] already noted that “child-labor” and “premature descolarisation” are connected with health shocks, suggesting that child-income indeed plays the role of an insurance asset, with repayments contingent on a bad event. The recent paper of Maccini and Yang[19] is clearly in the same direction, although connecting schooling decision to other types of shock (rainfall shocks) and focusing on the asymmetric effect between girls and boys in the household (as in Duflo[6]). More generally, if we extend the analysis to fields outside schooling choice, numerous authors, as Fafchamps[8], Harrower and Hoddinott[15] and Park (2006), consider that shocks are insured through risk sharing ”networks” (not only household) and that ”remittances” of labor-income act as contingent repayments in case of negative shocks (see Gertler and Gruber[11], Conroy et al.[4]). These intra-community transfers are more or less compulsory, due to the need of reciprocity in the co-insurance system of the network (Fafchamps[8], or due to social punishment (Rapoport and Docquier[25]).

In the following, we will first present a theoretical model to obtain testable predictions on the relationship between health shock (on adults) and child education once we fully consider that child education is an insurance asset, presenting the property of a “changing appropriation” in case of bad event. We will be able to reinterpret, secondly, the impact of the health shock on educational choice of households in a totally new manner which allows dealing with data and empirical findings not compatible with the prior view that a health shock is, always and elsewhere, a negative thing for education of children.

2 Theoretical Model

In this section we build a simple theoretical model to highlight the role of child income appropriation on the relationship between education and illness prevalence. To do so, we consider the problem of a representative household composed of a head (the parent) and a child in a two period model[2].

During the first period (activity period), the parent have a sure revenue ω and choose the proportion of time they educate their child (t). When not enrolled in the educational system (that is in a proportion $(1-t)$ of the period) children earn for the household a wage ω^i that can differ among children (according to gender for example). The time spent to education allows to increase this

[2]The model is easily extendable to situations where the revenue of the parent comes from its own parent choice (in term of education). Results are robust to such an overlapping generation modeling.

"basic" wage in second period. We note ρ the return from each unit of time spent on education, so that choosing t in period one gives as child income $(1-t)\omega^i$ in period one, and $(1+\rho t)\omega^i$ in period two.

Health/HIV risk takes place in first period, after the choice of education. We model health risk as a binomial risk of wealth. With probability p, the parent fall sick for the two periods (for the sake of simplicity, we assume that no seropositivity declares in second period ; and consistently with the pattern of HIV-AIDS). He then lose an amount ε_1 of his revenue in the first period, and an amount ε_2 in the second.

We model the second period as a retirement period. During this period, the parent doesn't earn money by his own and rely on appropriation of his child income (accordingly with the literature on old-age security). Therefore, whereas, in first period bad health status also encompasses a loss of revenue, in second period the loss reduce to health cost. We then assume $\varepsilon_1 > \varepsilon_2$: the monetary cost of illness is higher in first period than in second.

Still, in second period, the parent can appropriate a proportion of their child revenue. The key mechanism of our model comes from the assumption that the proportion of child income that can be appropriated by the parent differs depending on the health status and differ among children (according to gender – as documented in Maccini and Yang[19] or Duflo[6] – for example). More precisely, we assume that the parent appropriates a proportion δ of his child revenue if healthy and a proportion $\delta + \Delta^i$ if sick, where Δ^i can be heterogenous.

Letting β be the discount factor between the two periods, the problem of the parent choosing t in period 1 writes:

$$\begin{aligned} \max_t \quad & p\left[u\left(\underline{C_1}\right) + \beta u\left(\underline{C_2}\right)\right] + (1-p)\left[u\left(\overline{C_1}\right) + \beta u\left(\overline{C_2}\right)\right] \qquad (1) \\ \text{where} \quad & \overline{C_1} = (1-t)\omega^i + \omega \\ & \underline{C_1} = (1-t)\omega^i + \omega - \varepsilon_1 \\ & \overline{C_2} = \delta(1+\rho t)\omega^i \\ & \underline{C_2} = (\delta + \Delta^i)(1+\rho t)\omega^i - \varepsilon_2 \end{aligned}$$

For the model to remain tractable and realistic, we moreover assume that, if healthy, the parent is always richer in the first than in the second period, that is $\overline{C_1} > \overline{C_2}$ (which corresponds to $\omega > \delta(1+\rho)\omega^i$) and always better off healthy then ill, that is $\overline{C_1} > \underline{C_1}$ and $\overline{C_2} > \underline{C_2}$ (what can be written as $\Delta^i(1+\rho)\omega^i < \varepsilon_2$).

To capture the role of "changing appropriation", let us first analyze the baseline model where appropriation is the same in the two states of nature ($\Delta^i = 0$) and to compare it with the case where, through appropriation, education can have an insurance role ($\Delta^i > 0$). This will allow us, to show that, if optimal education is decreasing with illness prevalence in the baseline case, the asymmetric feature of appropriation can lead to a positive relationship.

2.1 The benchmark case: no insurance role for education ($\Delta^i = 0$)

Let us first assume that appropriation of child income by the parent doesn't increase in case of illness, that is $\Delta^i = 0$. In this case, the first order condition of (1) writes:

$$-p\omega_i u'\left(\underline{C_1}\right) + \beta p\delta\rho\omega^i u'\left(\underline{C_2}\right) - (1-p)\omega_i u'\left(\overline{C_1}\right) + \beta(1-p)\delta\rho\omega^i u'\left(\overline{C_2}\right) = 0$$

That is:

$$\frac{\mathbb{E}(u'(C_1))}{\mathbb{E}(u'(C_2))} = \beta\delta\rho$$

To analyze the effect of illness prevalence p on the optimal t, let us define

$$f(t,p) \equiv \frac{\mathbb{E}(u'(C_1))}{\mathbb{E}(u'(C_2))} - \beta\delta\rho$$

and use the Implicit Function Theorem:

$$\frac{\partial t}{\partial p} = -\frac{\partial f/\partial p}{\partial f/\partial t}$$

Now,

$$\begin{aligned}\frac{\partial f}{\partial p} &= \frac{\left(u'\left(\underline{C_1}\right) - u'\left(\overline{C_1}\right)\right)\mathbb{E}(u'(C_2)) - \left(u'\left(\underline{C_2}\right) - u'\left(\overline{C_2}\right)\right)\mathbb{E}(u'(C_1))}{\left[\mathbb{E}(u'(C_2))\right]^2} \\ &= \frac{u'\left(\underline{C_1}\right)u'\left(\overline{C_2}\right) - u'\left(\overline{C_1}\right)u'\left(\underline{C_2}\right)}{\left[\mathbb{E}(u'(C_2))\right]^2} \end{aligned} \tag{2}$$

When $\Delta^i = 0$, $\underline{C_2} = \delta(1+\rho t)\omega^i - \varepsilon_2$ and $\overline{C_2} - \underline{C_2} = \epsilon_2$ whatever t. As $\overline{C_1} - \underline{C_1} = \epsilon_1\ \forall t$, this means that the income risk faced the parent is independent from the level of education he chooses for his child. Therefore, in the case, the educational choice reduce to wealth transfer between the two period. To abstract for the second order effect of wealth on risk aversion, let us consider the case of Constant Absolute Risk Aversion (CARA) preferences:

$$u(C) = -\frac{1}{\alpha}e^{-\alpha C}$$

It then turns out that:

Proposition 1. *If the proportion of child revenue appropriated by the parent doesn't raise is case of illness ($\Delta^i = 0$), the level of education (t) decreases with illness prevalence (p).*

Proof. See Appendix A. □

This theoretical result is a direct consequence of the income effects and intertemporal smoothing decisions obtained in this framework. Health shock implies, first of all, an impoverishment of households, with income-losses of ϵ_1 and ε_2. For $\epsilon_1 > \varepsilon_2$, we have that the education decision is downsized in face of diseases, to compensate potential income-loss in period 1. Empirically, the slope between health risk (p) and level of education (t) is negative, a result already obtained by Fortson [10], using a different micro modeling (human capital decision and mortality risk).

2.2 Assume an insurance role for education ($\Delta^i > 0$)

If we now assume the part of child revenue appropriated in period 2 by the parent is higher in case of illness $\Delta^i > 0$, the first order condition of program (1) becomes:

$$g(t,p) \equiv \frac{\mathbb{E}(u'(C_1)) - p\beta\Delta^i\rho u'(\underline{C_2})}{\mathbb{E}(u'(C_2))} - \beta\delta\rho = 0$$

with,

$$\begin{aligned}
\frac{\partial g}{\partial p} &= \frac{\partial f}{\partial p} - \frac{\beta\Delta^i\rho u'(\underline{C_2})\mathbb{E}(u'(C_2)) - p\beta\Delta^i\rho u'(\underline{C_2})(u'(\underline{C_2}) - u'(\overline{C_2}))}{[\mathbb{E}(u'(C_2))]^2} \\
&= \frac{u'\left(\underline{C_1}\right)u'\left(\overline{C_2}\right) - u'\left(\overline{C_1}\right)u'\left(\underline{C_2}\right) - \beta\Delta^i\rho u'(\underline{C_2})u'(\overline{C_2})}{[\mathbb{E}(u'(C_2))]^2} \qquad (3)
\end{aligned}$$

Notice here that two forces are at stakes when comparing (3) and (11): (i) an extra negative term appears at the numerator and (ii) Δ^i (positive) increases $\underline{C_2}$ so that we now have $\underline{C_2} > \overline{C_2} - \varepsilon_2$. On the one hand, education has a higher return (for the parent) due to extra-appropriateness (i) ; but on the other, the extra (expected) wealth in second period reduce the need for education for intertemporal consumption smoothing purpose (ii).

Moreover

$$\frac{\partial g}{\partial t} = \frac{\partial f}{\partial t} - \frac{p\beta\Delta^i\rho(\delta+\Delta^i)\rho\omega^i u''(\underline{C_2})\mathbb{E}(u'(C_2)) - p\beta\Delta^i\rho u'(\underline{C_2})\left[p(\delta+\Delta^i)\rho\omega^i u''(\underline{C_2}) + (1-p)\delta\rho\omega^i u''(\overline{C_2})\right]}{[\mathbb{E}(u'(C_2))]^2}$$

That simplifies in the case of CARA utility function into:

$$\frac{\partial g}{\partial t} = \frac{\partial f}{\partial t}_{|\Delta^i=0} - \frac{p\Delta^i\rho\omega^i}{[\mathbb{E}(u'(C_2))]^2}\left\{u''\left(\underline{C_2}\right)\mathbb{E}\left(u'\left(C_1\right)\right) + (1-p)\beta\rho\Delta^i u''(\underline{C_2})u'(\overline{C_2})\right\} > 0$$

We therefore end up with,

$$\frac{\partial t}{\partial p} = \frac{1}{\omega^i}\frac{u'\left(\underline{C_1}\right)u'\left(\overline{C_2}\right) - u'\left(\underline{C_2}\right)\left[u'\left(\overline{C_1}\right) + \beta\Delta^i\rho u'(\overline{C_2})\right]}{\mathbb{E}(u''(C_1))\mathbb{E}(u'(C_2)) + \delta\rho\mathbb{E}(u''(C_2))\mathbb{E}(u'(C_1)) + p\Delta^i\rho\omega^i\left[u''\left(\underline{C_2}\right)\mathbb{E}(u'(C_1)) + (1-p)\beta\rho\Delta^i u''(\underline{C_2})u'(\overline{C_2})\right]} \qquad (4)$$

that leads to the following proposition

Proposition 2. *When the proportion of child revenue appropriated by the parent is higher in case of illness ($\Delta^i > 0$), the level of education decreases with illness prevalence (in the case of CARA preferences) if and only if agents are impatient enough, that is if and only if*

$$\beta < \frac{1}{\Delta^i \rho} \left[\frac{u'(\underline{C_1})}{u'(\underline{C_2})} - \frac{u'(\overline{C_1})}{u'(\overline{C_2})} \right] \equiv \overline{\beta}$$

In the other case, that is if $\beta > \overline{\beta}$ (with $\overline{\beta} > 0$ whenever $\epsilon_1 > \epsilon_2$), the level of education increases in p.

Remark 1. *The role of changing appropriateness (that is the "insurance role" of education) can be inferred from this condition. When Δ^i is positive, we obtain that the negative slope between prevalence and education (found when $\Delta^i = 0$, see Proposition 1) is more difficult to obtain. For high level of β ($\beta > \overline{\beta}$), we even found that the sign changes and that the slope becomes positive.*

The intuition behind this result is pretty simple. Assuming a change in the degree of appropriateness following a bad health realization gives education an insurance role. This therefore calls for an increase in education when risk increases. The total effect of an increase in illness prevalence results from a tradeoff between this "insurance effect" and the consumption smoothing effect found in the previous section. According to proposition 2, the insurance effect dominates when the discount factor is large enough, that is when the weight of second period (the one in which education plays its insurance role) is large enough in the intertemporal utility function.

These theoretical results (Propositions 1 and 2) provides us with interesting testable predictions. Indeed, data would confirm these mechanisms if, after proxying health risk, we find that (i) the relationship between health risk and education is generally negative, but (ii) can become positive when the insurance role for education is important, for example for groups that are highly appropriable. In the next sections, we test for this kind of predictions on data assuming that some children or parents characteristics can lead to different value of Δ^i, that is to heterogeneity in the insurance role of education.

3 Data

We use the nationally representative cross-sectional data set, the Demographic and Health Survey (DHS), for 17 Sub-Saharan African countries, namely Burkina Faso(2003), Cameroon(2004), Congo Kinshasa(2007), Ethiopia(2005), Ghana(2003), Guinea(2005), Kenya(2008/09), Lesotho(2009), Liberia(2007), Malawi(2010), Mali(2006), Niger(2006), Senegal(2005), Sierra Leone(2008), Swaziland(2006/07), Zambia(2007) and Zimbabwe(2005/06). In this survery data is collected at both the individual and household level. The DHS has been conducted in developing countries since 1984 with the aim of providing countries with data needed to monitor and evaluate population, health and nutrition programmes on a regular basis. The data is collected ususally every 5 years though some are collected a few years earlier. It contains household data on basic characteristics of members of each household and also specific data on both male and female household members between the ages 15 and 49 inclusive. Some surveys include testing for the HIV/AIDS status of members of the household 15 to 49 years of age and these are the data sets we use. The sampling frame used in most DHS is, by definition, a list of non-overlapping area units with a majority of DHS sample designs clustered and stratified.

We are interested in measuring the impact that HIV prevalence at the community level affects educational enrollment. We focus on individuals between the ages of 6 and 22 inclusive. Thus we have for our analysis 357873 individuals within 128575 households nested in 6814 communities which are in turn nested in 17 countries. If we split the data into 3 age groups: 6 to 12, 13 to 18 and 19 to 22, we have that our sample of 6 to 22 year olds is made up of 51.22% 6 to 12 year olds, 32.60% of 12 to 18 year olds and 16.18% individuals of university going age. We use these age groups later because we expect the community HIV prevalence rates will have differing effects depending on the educational group of the child.

Age Group	**Frequency**	**Percentage**
6 to 12	186, 254	51.22
13 to 18	118, 530	32.60
19 to 22	58, 823	16.18
Total	363, 607	100.00

Table 1: Age Group

	No Education	**Primary**	**Secondary**	**Higher**	**Total**
6 to 12	38.79	60.78	0.43	0.00	100.00
13 to 18	23.57	53.17	23.18	0.08	100.00
19 to 22	28.66	32.40	36.66	2.27	100.00
Total	32.18	53.70	13.72	0.39	100.00

Table 2: Highest Educational Level of Individuals Per Age Group

By educational group we mean primary, secondary or university. Table 2. looks at the split of sample based on both age and educational level. Note that in the sample we drop all individuals who are less than 11 years but are in secondary school and those less than 17 years who are in the university. We therefore have that of the 6 to 12 year olds, about 60.78% of them are in primary school while 38.79% have no education. Of the 13 to 18 year olds, 53.17% of them have only primary school education with 23.18% having some level of secondary school education. Finally what is clear is that while most of the 19 to 22 year olds have some level of education, only a few, namely 2.27% of them have some university education. About 28.66% of 19 to 22 year olds have no education whatsoever. Of our sample of 6 to 22 year olds we remove all children from households whose heads age is below 15. We also drop children whose age does not match with thier educational level.

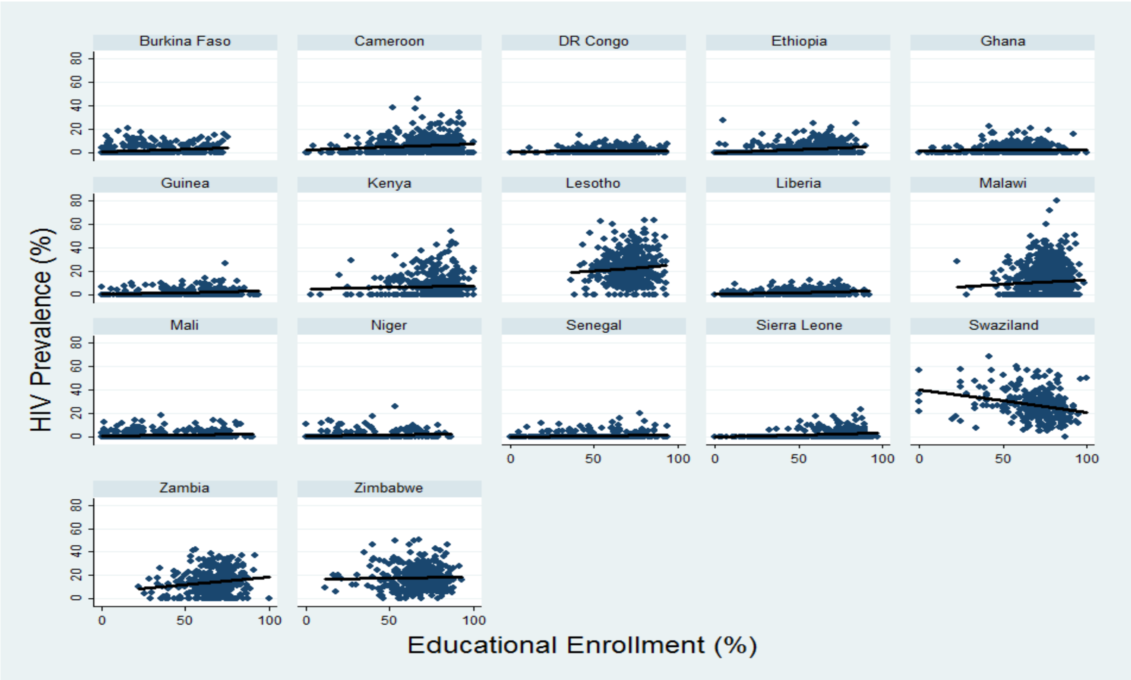


Figure 1: Community Enrollment vs Prevalence Per Country

Finally we take a look at the relationship between the HIV prevalence rates and enrollment rates at both the country and community levels[3]. The HIV prevalence rates are calculated using individuals between the ages of 15 and 49 years inclusive. The tables are population weighted. The size of the population in the year of interview is used for each country together with the sample weight from the survey to create the required population weights. There exists a clear positive relationship between enrollment rates and prevalence rates in countries such as Lesotho and Malawi. Note that both countries can be found in Southern Africa, the region where HIV first originated. These countries are however also some of the most developed in Africa, so it is reasonable that they have both high prevalence and high enrollment rates. The relation appears to be borderline insignificant for most of the West African countries where the linear fit appears almost flat. If we however take a look at a country such as Swaziland we have that the effect is actually negative. Thus controlling for country fixed effects it appears that the relationship between HIV prevalence and educational enrollment rates at the community level is not given. It can be either positive negative or insignificant. It is this relationship between education and HIV that we explain using the insurance motive.

One of the tests we run in our empirical model is to find out if living in the rural area as opposed to an urban area has an impact on the relationship between community HIV prevalence and educational enrollment. What we expect is that the relationship will be negative in urban areas

[3]The aggregate relation at the community level can be found in the appendix

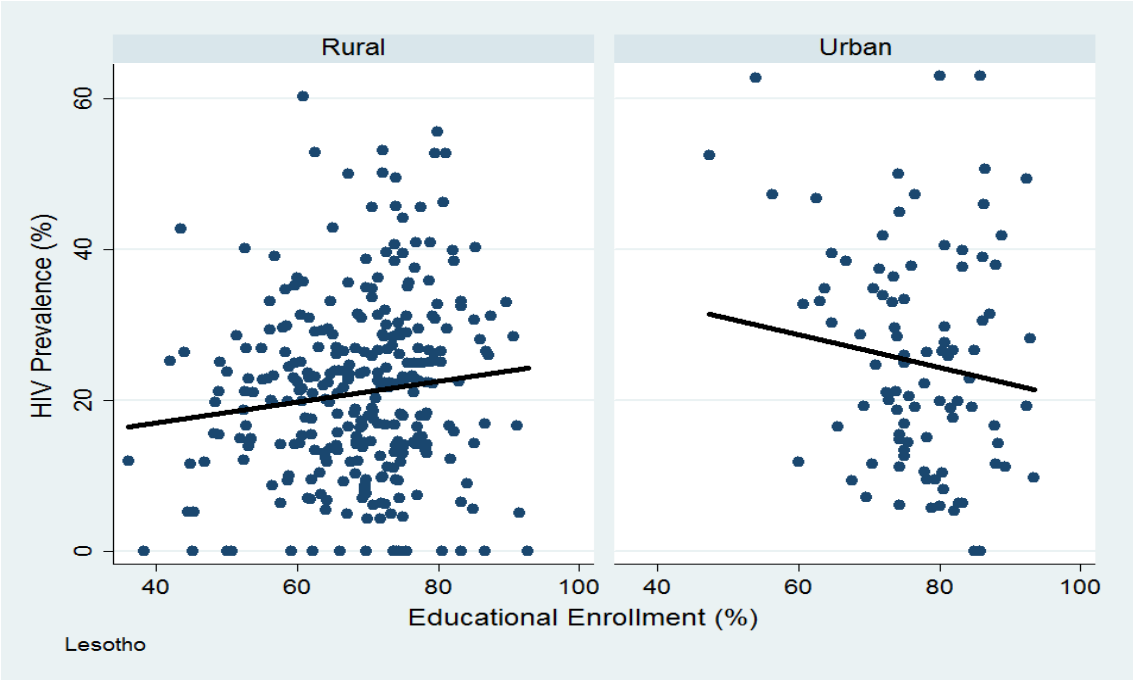


Figure 2: Community Enrollment vs Prevalence Over Type of Place of Residence for Lesotho

but positive in rural areas as appropriation is easier when children live in rural areas than when they live in urban areas. Figure 2 takes a first look at his relation for Lesotho. In Lesotho, the relation between community prevalence and educational enrollment is either positive or negative depending on the type of place of residence. In figure 1 we have that the overall effect seems to be positive but when we take type of place of residence into account, the relation becomes positive in rural areas where appropriation of child income is much easier than in urban areas where such appropriation is a bit difficult. In our analysis we use prevalence rates at the community level as we expect that the community in which a child lives will have a direct impact on their enrollment in school. In addition to community prevalence rates and country enrollment rates we also include child characteristics and household characteristic variables.

- **Child characteristics:** Age, gender, residency status and relation to head.
- **Household characteristics:** Proportion of children below 5, type of place of residence, income, gender of head, age of head, HIV status of the household and educational level of head.

The average age is 12.85 years with an almost equal number of males and females. Most of the children are usual residents of their households with a little over half being children of the head of the household. Households have about 16.85% of their children below the ages of 5. Approximately 69.07% of households are located in rural areas with 74.14% of the households being headed by males. About 43.93% of the household heads are uneducated, while 5.9801% of the households have an

Variable	N	Mean	Std Dev
Age	363607	12.8557	4.7883
Male	363592	0.4979	0.5000
Usual Resident	363351	0.9746	0.1574
Child of Head	363532	0.6256	0.4840
Prop. of Children < 5	130165	0.1685	0.1560
Rural	130165	0.6907	0.4622
Male Head	130165	0.7414	0.4379
Head 40 - 59 years	130165	0.3968	0.4892
Head 60 - 79 years	130165	0.1778	0.3823
Head $\geq$ 80 years	130165	0.0205	0.1416
Middle Income	130165	0.2004	0.4003
High Income	130165	0.4125	0.4923
Household HIV+	130165	0.0598	0.2371
Household HIV Status Unknown	130165	0.5149	0.4998
Head Uneducated	129081	0.4393	0.4963

Table 3: Summary Statistics

HIV+ member. We next focus on the empirical model we use to analyse the impact of community HIV prevalence on enrollment rates.

4 Empirical Model

Following our theoretical model, we now want to analyze the effect of HIV risk, proxied by community level HIV prevalence, on education, the attendance status of children. Recall that our theoretical model predicts that this effect is generally negative but can turn out to be positive for households in which the part of child income appropriated increases in case of bad health status (this intuition being that is it more likely among highly appropriable children). To study the impact of community HIV prevalence on the school attendance status of a child we use a multilevel model. The multilevel model allows us to take into account random components at the household, community and country level. As our data is hierarchical in nature, ignoring the clustering will imply that the independence condition is violated. In such a case, the standard errors are underestimated[14]. The hierarchical structure in our data comes from the fact that we pool our data across countries and also from the design of the DHS, where individuals are nested within households which are in turn nested within communities which are also nested within countries. Due to the complex nature of our analysis, 4 levels, we do a preliminary test of the significance of the levels. We are able to include contextual HIV/AIDS factors at the community level. We observe y_{ijkl}, the enrollment status of individual i in household j in community k in country l where

$$y_{ijkl} = \begin{cases} 1 & \text{if currently enrolled or was enrolled in current year} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Let us denote by p_{ijlk} the probability that $y_{ijkl} = 1$ that is:

$$p_{ijkl} = Pr\left(y_{ijkl} = 1\right)$$

Then by denoting $\pi_{ijkl} = \ln\left(\frac{p_{ijkl}}{1-p_{ijkl}}\right)$ we have that

$$\pi_{ijkl} = \alpha_0 + \alpha X_{ijkl} + \beta Z_{jkl} + \gamma W_{kl} + \eta V_1 + \upsilon_{jkl} + \epsilon_{kl} + \phi_l \tag{6}$$

where α_0 is the intercept which varies randomly, α is the vector of coefficients for the covairates X_{ijkl}, β is the vector of coefficients associated with the covariates Z_{jkl}, γ the vector of coefficients for covariates W_{kl} and η the vector of coefficients for covariates V_l. The covariates, X_{ijkl} vary at the individual level, Z_{jkl} varies at the household level and W_{kl} at the community level. The error terms at the household, community and country levels are given as υ_{jkl}, ϵ_{kl} and ϕ_l respectively and have means 0 and variances, σ^2_{hh}, σ^2_{cm} and σ^2_{ct} respectively, see [13]. To decide what levels are indeed necessary, we first calculate the intraclass correlations. This variable is calculated from the empty model:

$$\pi_{ijkl} = \alpha_0 + \upsilon_{jkl} + \epsilon_{kl} + \phi_l \tag{7}$$

Estimates of household, community and country level variances are used to calculate the intra-class correlation coefficient to determine the proportion of group-level variance compared to total variance, using the following formula:

$$\rho_{hh} = \frac{\sigma^2_{hh}}{\sigma^2_{hh} + \sigma^2_{cm} + \sigma^2_{ct} + \sigma^2_{in}} \tag{8}$$

$$\rho_{cm} = \frac{\sigma^2_{rg}}{\sigma^2_{hh} + \sigma^2_{cm} + \sigma^2_{ct} + \sigma^2_{in}} \tag{9}$$

and

$$\rho_{ct} = \frac{\sigma^2_{ct}}{\sigma^2_{hh} + \sigma^2_{cm} + \sigma^2_{ct} + \sigma^2_{in}} \tag{10}$$

where ρ_{hh}, ρ_{cm} and ρ_{ct} are the intra-class correlations at the household, community and country levels and σ^2_{in} is the variance at the individual level, where for the case of a multilevel logistic regression is fixed at $\frac{\pi^2}{3}$, i.e. 3.289 (see Hedeker and Gibbsons[16]).

The empty model gives us as variances for the four levels $\sigma^2_{in} = 3.2899$, $\sigma^2_{hh} = 0.7017$, $\sigma^2_{cm} = 0.9317$ and $\sigma^2_{ct} = 0.7487$. From equation (8) we obtain as intra-class correlation rates $\rho_{hh} = 12.3713$, $\rho_{cm} = 16.4263$ and $\rho_{ct} = 13.1999$ meaning that 12.3713% of the total variation is explained at the household level, with 16.4263% explained at the community level and 12.3713% at the country level. Based on this result, we include the four levels in our multilevel model. We now discuss the results we obtain from our multilevel model.

5 Results

Running our empirical model on Demographic and Health Surveys, we are first able to confirm previous findings. We indeed find that (i) having an HIV+ household member implies a negative impact on the probability of enrolling in school, a result that can be reconciled with Fortson[10] (ii) living in rural areas also has a negative and significant effect on enrollment whereas (iii) being from a high income household has a positive and significant impact on the probability of being enrolled. Regarding, our variable of interest, we first find that, taking into account the whole sample, the probability of being enrolled in school is not significantly affected by the probability of adult household members becoming HIV+. However is we first split the data based on the level of prevalence, i.e. high versus low, we find that the effect is significantly positive for countries with low HIV prevalence though it remains insignificant but negative for countries with high HIV prevalence.

The results become more nuanced if, as in Nugent[23], and based on the second part of the theoretical model (allowing for heterogenous appropriateness), we split our data based on gender and on type of place of residence of the household. An increase in HIV prevalence (the probability

Fixed Effects										
Variable	**Total**	**Male**	**Female**	**Urban**	**Rural**	**6 - 12**	**13 - 18**	**19 - 22**	**Low Prevalence**	**High Prevalence**
Intercept	-3.3371^{***}	-2.4997^{***}	-3.6439^{***}	-1.7544^{***}	-4.8271^{***}	-3.4162^{***}	-3.2379^{***}	-2.5942^{***}	-3.1362^{***}	-2.9248^{***}
	(0.1397)	(0.0853)	(0.2626)	(0.3045)	(0.1768)	(0.6458)	(0.3262)	(0.6636)	(0.1321)	(0.2992)
Age	1.1302^{***}	1.1362^{***}	1.1719^{***}	0.9639^{***}	1.2402^{***}	2.9692^{***}	0.7783^{***}	-2.5452^{***}	1.0722^{***}	1.2356^{***}
	(0.0069)	(0.0094)	(0.0105)	(0.0119)	(0.0086)	(0.0391)	(0.1019)	(0.5104)	(0.0080)	(0.0140)
Age-Squared	-0.0480^{***}	-0.0464^{***}	-0.0517^{***}	-0.0410^{***}	-0.0528^{***}	-0.1406^{***}	-0.0395^{***}	0.0520^{***}	-0.0445^{***}	-0.0552^{***}
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0022)	(0.0033)	(0.0125)	(0.0003)	(0.0005)
Male	0.4530^{***}			0.5300^{***}	0.4173^{***}	0.1929^{***}	0.6193^{***}	0.8772^{***}	0.5416^{***}	0.1860^{***}
	(0.0098)			(0.0180)	(0.0117)	(0.0152)	(0.0170)	(0.0265)	(0.0114)	(0.0202)
Usual Resident	0.1763^{***}	0.2892^{***}	0.0493	0.2249^{***}	0.0916^{**}	0.1444^{*}	0.1801^{***}	-0.3535^{***}	0.1085^{**}	0.0856^{*}
	(0.0330)	(0.0486)	(0.0458)	(0.0582)	(0.0404)	(0.0767)	(0.0491)	(0.0561)	(0.0476)	(0.0486)
Child of Head	0.6871^{***}	0.4069^{***}	0.8397^{***}	0.8605^{***}	0.5921^{***}	0.4001^{***}	0.8078^{***}	0.6162^{***}	0.6996^{***}	0.7241^{***}
	(0.0120)	(0.0166)	(0.0169)	(0.0206)	(0.0147)	(0.0204)	(0.0198)	(0.0313)	(0.0142)	(0.0233)
Household HIV+	-0.0487^{*}	-0.0683^{*}	-0.0281	0.0122	-0.0877^{***}	-0.0501	-0.0806^{*}	-0.2088^{***}	-0.0176	-0.0900^{***}
	(0.0274)	(0.0362)	(0.0368)	(0.0467)	(0.0337)	(0.0468)	(0.0413)	(0.0556)	(0.0599)	(0.0340)
Household HIV Unknown	-0.0266^{**}	-0.0063	-0.0388^{**}	-0.0150	-0.0337^{**}	-0.0410^{**}	-0.1021^{***}	-0.0088	-0.0211	-0.0594^{**}
	(0.0129)	(0.0164)	(0.0174)	(0.0244)	(0.0152)	(0.0193)	(0.0198)	(0.0288)	(0.0147)	(0.0285)
Rural	-0.8149^{***}	-0.8188^{***}	-0.8352^{***}			-1.1558^{***}	-0.7229^{***}	-0.6304^{***}	-1.0414^{***}	-0.2272^{***}
	(0.0312)	(0.0336)	(0.0363)			(0.0450)	(0.0381)	(0.0423)	(0.0392)	(0.0498)
Middle Income	0.3195^{***}	0.3155^{***}	0.3739^{***}	0.2657^{***}	0.3616^{***}	0.4307^{***}	0.4437^{***}	0.1872^{***}	0.3289^{***}	0.3351^{***}
	(0.0171)	(0.0217)	(0.0229)	(0.0565)	(0.0180)	(0.0248)	(0.0260)	(0.0421)	(0.0200)	(0.0340)
High Income	0.7941^{***}	0.8002^{***}	0.8855^{***}	0.9762^{***}	0.7527^{***}	1.0130^{***}	0.8784^{***}	0.8174^{***}	0.7943^{***}	0.8823^{***}
	(0.0192)	(0.0300)	(0.0257)	(0.0522)	(0.0211)	(0.0287)	(0.0287)	(0.0410)	(0.0226)	(0.0378)
Prop. of Child. < 5	-0.8896^{***}	-0.0335	-1.3894^{***}	-1.5303^{***}	-0.6006^{***}	-0.0785	-1.0899^{***}	-2.6911^{***}	-0.6944^{***}	-1.4031^{***}
	(0.0462)	(0.0629)	(0.0624)	(0.0876)	(0.0543)	(0.0710)	(0.0753)	(0.1069)	(0.0546)	(0.0907)
Head Uneducated	-0.7298^{***}	-0.7720^{***}	-0.7910^{***}	-0.9386^{***}	-0.6136^{***}	-0.9036^{***}	-0.8728^{***}	-0.8385^{***}	-0.7500^{***}	-0.6491^{***}
	(0.0158)	(0.0201)	(0.0210)	(0.0289)	(0.0188)	(0.0236)	(0.0236)	(0.0350)	(0.0185)	(0.0315)
Head 40-59	0.1765^{***}	0.1341^{***}	0.2147^{***}	0.2731^{***}	0.1235^{***}	0.0014	0.2395^{***}	0.6403^{***}	0.1878^{***}	0.1811^{***}
	(0.0144)	(0.0190)	(0.0195)	(0.0262)	(0.0172)	(0.0214)	(0.0242)	(0.0375)	(0.0171)	(0.0282)
Head 60-79	0.2958^{***}	0.2051^{***}	0.3758^{***}	0.3917^{***}	0.2308^{***}	0.0676^{**}	0.3239^{***}	0.6862^{***}	0.2537^{***}	0.4100^{***}
	(0.0184)	(0.0239)	(0.0249)	(0.0352)	(0.0217)	(0.0289)	(0.0285)	(0.0432)	(0.0219)	(0.0362)
Head > 80	0.4318^{***}	0.3225^{***}	0.5504^{***}	0.6588^{***}	0.3078^{***}	0.2274^{***}	0.5024^{***}	0.6635^{***}	0.4326^{***}	0.4312^{***}
	(0.0426)	(0.0551)	(0.0568)	(0.0916)	(0.0482)	(0.0670)	(0.0610)	(0.0958)	(0.0515)	(0.0790)
Head Male	-0.2703^{***}	-0.2368^{***}	-0.3440^{***}	-0.2600^{***}	-0.2552^{***}	-0.2526^{***}	-0.2967^{***}	-0.2743^{***}	-0.2929^{***}	-0.2225^{***}
	(0.0146)	(0.0194)	(0.0195)	(0.0258)	(0.0172)	(0.0235)	(0.0219)	(0.0302)	(0.0182)	(0.0259)
Cluster HIV Prevalence	0.0009	-0.0035^{**}	0.0017	-0.0051^{**}	0.0108^{***}	0.0121^{***}	-0.0031	-0.0065^{***}	0.0380^{***}	-0.0025
	(0.0017)	(0.0016)	(0.0021)	(0.0024)	(0.0023)	(0.0027)	(0.0021)	(0.0023)	(0.0083)	(0.0022)
Country Enrollment Rate	0.0624^{***}	0.0570^{***}	0.0693^{***}	0.0271^{***}	0.0758^{***}	0.0892^{***}	0.0635^{***}	0.0186^{*}	0.0610^{***}	0.0567^{***}
	(0.0023)	(0.0010)	(0.0044)	(0.00582)	(0.0029)	(0.0109)	(0.0055)	(0.0112)	(0.0021)	(0.0048)
Random Effects										
Household										
Int. Variance	1.0133	0.9574	0.9006	1.1560	0.9283	1.52714	0.7429	0.4828	1.0164	1.1390
Int. Std. Deviation	1.0066	0.9784	0.9490	1.0752	0.9635	1.2358	0.8619	0.6948	1.0082	1.0673
Community										
Int. Variance	0.8990	0.8651	1.0008	0.3874	0.9538	1.4231	0.9406	0.6329	0.9899	0.5351
Int. Std. Deviation	0.9481	0.9301	1.0004	0.6224	0.9766	1.1929	0.9698	0.7956	0.9950	0.7315
Country										
Int. Variance	0.0173	-	0.0744	0.0963	0.0290	0.4925	0.1188	0.5212	0.0113	0.0765
Int. Std. Deviation	0.1317	-	0.2728	0.3103	0.1703	0.7018	0.3447	0.7219	0.1064	0.2766
Number of Obs.	357873	178561	179332	105563	252310	184164	116685	57024	255785	102088
Groups: Household	128575	93002	101415	37060	91515	94988	73415	46124	88929	39646
Groups: Cluster	6814	6812	6810	2291	4523	6802	6802	6773	4607	2207
Groups: Country	17	17	17	17	17	17	17	17	17	17

Table 4: Impact of HIV Prevalence

of adult household members becoming HIV+) leads to a reduction in male enrollment but an increase in female children enrollment, though the effect for females are insignificant. According to our theoretical, this would come from the fact that females are more appropriable than their male counterparts. The result can be related to the findings of Maccini and Yang [19] who advocate that girls are often used as insurance assets (in the case of rainfall shocks for Maccini and Yang [19]).

The same kind of results can be inferred from the split between urban and rural regions. As children are more easily appropriable in rural regions, we find that an increase in HIV-prevalence decreases the probability of enrollment in urban areas but increase it in rural areas. These two results on subsamples confirm the predictions of our theoretical model, as we find that for subgroup of children that are highly appropriable (female children and children in rural areas), the insurance role of education can lead to a positive and significant relationship between the probability of becoming HIV+ and the probability of being enrolled in school.

As a final check we split the data based on the age groups. We find that for individuals of university going age, an increase in the probability of becoming HIV+ leads to a significant decrease in the probability of being enrolled in school. The effect is however negative but insignificant for children of middle school going age. It is however positive and significant for children of primary school going age.

6 Discussion and Conclusion

We proposed to analyze the impact of health, and specifically HIV/AIDS, on education taking into account the fact that education of children can act as a form of insurance against shocks, and in this particular case, health shocks in old-age. We first built a theoretical model where active adults invest in the education of their children. We found that in the absence of extra appropriation in case of illness, an increase in the probability of falling sick leads to a reduction in the time children spent in school. However where there is a possibility for extra appropriation covering illness events, we have that health risk may in some cases lead to an increase in the amount of education, especially when the extra amount appropriable is very high.

We then test this idea, that in fact an increase in the probability of falling ill can lead to an increase in educational investments and find that for the overall population of 6 to 22 year old the effect is negative but that once the data is split between males and females the effect becomes positive for females, irrespective of whether we use a single-level (significant) or multilevel models (insignificant). When we also split the data between rural and urban households we find a positive and significant effect in the rural areas again irrespective of model used.

We therefore verify the classical result (a negative relationship between education and HIV prevalence, see Fortson [10]) for a subsample of children: male children and children living in urban areas; but enrich it for children of another type: female children and children in rural areas. Our interpretation of these results is that, depending on the appropriable pattern of children, education can act as an insurance asset: it provides protection in bad states. The theoretical model presented in the first part of the paper provides a possible rationalization of such a mechanism, even though we concede that several other theoretical reasonings may provide similar results, consistently with our empirical work.

Apart from the search for other theoretical explanations, our work calls for additional attention on the role of remittance systems. In our empirical setting, we have tried to proxy differences in appropriateness by some exogenous characteristics (gender, urban/rural areas) that have been proven in other papers to be related to appropriateness. Still, more attention need to be paid to our key mechanism of "changing appropriateness", for example by analyzing to what extend (and based on which characteristics) remittances change depending on the health status of parents.

References

[1] Basu, K. and H. van Pham (1998): "The Economics of Child Labor," The American Economic Review, 88(3), 412-427.

[2] Bazen, S. and C. Salmon (2008): "The Impact of Parental Health on Child Labor: Evidence from Bandladesh," GREQAM Working Paper Series No. 2008-65.

[3] Case, A. and C. Paxson (2010): "The Changing Role of Education in the AIDS Crisis," Center for Health and Wellbeing. Princeton University. Mimeo. August 2010.

[4] Conroy, A. C, M. J. Blackie, A. Whiteside, J. C. Malewezi and J. D. Sachs (2006): "Poverty, AIDS nad Hunger: Breaking the Poverty Trap in Malawi," Palgrave MacMillan, New York.

[5] Decron, S., J. Hoddinott and T. Woldehanna (2005): "Shocks and Consumption in 15 Ethiopian Villages 1999 - 2004," Journal of African Economies, 14(4), 559-585.

[6] Duflo, E. (2000): "Child Health and Household Resources in South Africa: Evidence from the Old Age Pension Program," The American Economic Review, 90(2), 393-398.

[7] Ehrlich, I. and F. T. Lui (1991): "Intergenerational Trade, Longevity, and Economic Growth," Journal of Political Economy, 95(5), 1029-1059.

[8] Fafchamps, M. (1992): "Solidarity Networks in Preindustrial Societies: Rational Peasants with a Moral Economy," Economic Development and Cultural Change, 41(1), 147-174.

[9] Flores, G. et al. (2008): "Coping with Healthcare Costs: Implications for the Measurement of Catastrophic expenditures and Poverty," Health Economics, 17(12), 1393-1412.

[10] Fortson, J. (2011):"Mortality Risk and Human Capital Investment: The Impact of HIV/AIDS in Sub-Saharan Africa," Review of Economics and Statistics, 93(1), February 2011, 1-15.

[11] Gertler, P. and J, Gruber. (2002):"Insuring Consumption against Illness," The American Economic Review, 92(1), 51-70.

[12] Gill, I., S. Khandker and R. Shahidur (1991):"How Structure of Production Determines the Demand for Human Capital?," The Worldbank Policy Research Working Paper Series, No. 724.

[13] Goldstein, H. (1991): "Nonlinear Multilevel Models with an Application to Discrete Response Data", Biometrika, 78, 45 - 51.

[14] Guo, G. and Zhao, H. (2000): "Multilevel Modelling for Binary Data", Annual Review of Sociology, 26, 441 - 462.

[15] Harrower, and J. Hoddinott (2005):"Consumption Smoothing in the Zone Lacustre, Mali," Journal of African Economies, 14(4), 489-519.

[16] Hedeker, D. and R. D. Gibbsons (1996):"MIXOR: A Computer Programme for Mixed Effects Ordinal Regression Analysis," Computer Methods and Programs in Biometrics, 49, 157-176.

[17] Hox, J. (2010):"Multilevel Analysis: Techniques and Applications," Quantitative and Methodology Series, Routledge, 2^{nd} Edition.

[18] Kwabata, D., K. Xu and G. Carrin (2002):"Preventing Impoverishment throught Protection against Catastrophic Health Expenditure.,"Bulletin World Health Organisation, 80(8), 612 - 630.

[19] Maccini, S. and D. Yang (2009):"Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall.," The American Economic Review, 99(3), 1006-1026.

[20] Magnani, E. and A.Rammohan (2011):"Competition for Care? Coresidence, Care-Giving and Children's Education," School of Economics, The University of New South Wales WP.

[21] McIntyre, D., M. Thiede, G. Dahlgren and M. Whitehead (2006):"What are the Economic Consequences for Households of Illness and of Paying for Healthcare in Low- and middle-income Country Contexts?,"Social Science and Medicine, 62, 858-865.

[22] Michel, P. and B. Wigniolle (2007):"On Efficient Child Making," Economic Theory, 31(2), 307-326.

[23] Nugent, J. B. (1985):"The Old Age Security Motive for Fertility," Population and Development Review, 11(2), 75-97.

[24] Park, C. (2006):"Risk Pooling between Households and Risk Coping Measure in Developing Countries: Evidence from Rural Bangladesh," Economic Development and Cultural Change, 54(2), 423-457.

[25] Rapoport, H. and F. Docquier (2006):"The Economics of Migrants' Remittances, on the Economics of Giving, Reciprocity and Altruism", in Kolm, S. and Jean Mercier Ythier(eds), Handbook of Economics of Giving, Altruism and Reciprocity 2, Chapter 17, 1135-1198.

[26] Russel, S. (1996):"Ability to Pay for Healthcare: Concepts and Evidence,"Health Policy Plan, 11(3), 219-237.

[27] Sauerborn, R., A. Adams and M. Hien, (1996):"Household Stratergies to Cope with the Economic Costs of Illness,"Social Science and Medicine, 43(3), 291-301.

[28] Schoonbroodt, A. and M. Tertilt (2010):"Who Owns Children and Does it Matter," NBER Working Paper 15663.

[29] Wagstaff, A. and Van Doorslaer, E. (2003): "Catastrophe and Impoverishment in Paying for Health Care: With Applications to Vietnam 1993-1998,"Health Economics, 12, 921-934.

[30] Xu, K. et al. (2003):"Household Catastrophic Heatlh Expenditure: A Multicountry Analysis,"Lancet, 362, 111-117.

[31] Yamano, T. and T.S. Jayne (2005):"Working-Age Adult Mortality and Primary School Attendance in Rural Kenya,"Economic Development and Cultural Change, 53(3), 619-653.

A Proof of Proposition 1

We have:

$$\begin{aligned}\frac{\partial f}{\partial p} &= \frac{\left(u'\left(\underline{C_1}\right) - u'\left(\overline{C_1}\right)\right)\mathbb{E}(u'(C_2)) - \left(u'\left(\underline{C_2}\right) - u'\left(\overline{C_2}\right)\right)\mathbb{E}(u'(C_1))}{\left[\mathbb{E}(u'(C_2))\right]^2} \\ &= \frac{u'\left(\underline{C_1}\right)u'\left(\overline{C_2}\right) - u'\left(\overline{C_1}\right)u'\left(\underline{C_2}\right)}{\left[\mathbb{E}(u'(C_2))\right]^2} \qquad (11)\end{aligned}$$

Therefore, $\frac{\partial f}{\partial p}$ is of the sign of $\frac{u'(\underline{C_1})}{u'(\overline{C_1})} - \frac{u'(\underline{C_2})}{u'(\overline{C_2})}$, that is, in the case of $\Delta_i = 0$, the sign of $\frac{u'(\overline{C_1}-\varepsilon_1)}{u'(\overline{C_1})} - \frac{u'(\overline{C_2}-\varepsilon_2)}{u'(\overline{C_2})}$

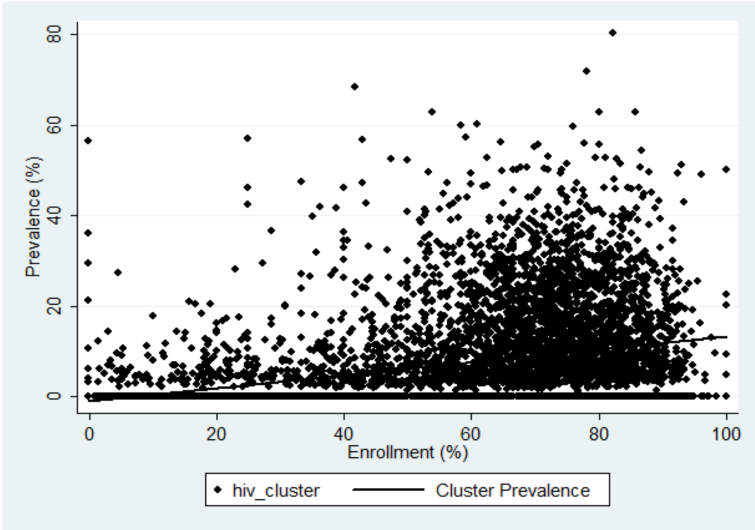
Noticing that $\frac{u'(C-\varepsilon)}{u'(C)}$ is constant in C in the case of Constant Absolute Risk Aversion, it turn out that: $\frac{u'(\overline{C_1}-\varepsilon_1)}{u'(\overline{C_1})} - \frac{u'(\overline{C_2}-\varepsilon_2)}{u'(\overline{C_2})} \geq 0$ as $\varepsilon_1 > \varepsilon_2$.

Lemma 1. *If $u(.)$ exhibits CARA, $\frac{\partial f}{\partial p}_{|\Delta_i=0} \geq 0$*

Note that the previous lemma also hold for preferences exhibiting Increasing Absolute Risk Aversion and that the result is ambiguous for Decreasing absolute risk aversion

As, moreover,

$$\frac{\partial f}{\partial t}_{|\Delta_i=0} = \frac{-\omega^i\mathbb{E}(u''(C_1))\mathbb{E}(u'(C_2)) - \delta\rho\omega^i\mathbb{E}(u''(C_2))\mathbb{E}(u'(C_1))}{\left[\mathbb{E}(u'(C_2))\right]^2} > 0$$



proposition 1 holds.

B Description of Variables

Variable	Measure
	Outcome Variable
Currently Enrolled	Coded as 1 if individual is currently enrolled or was enrolled in current year, 0 otherwise
	Explanatory Variables
Age	Age of Child centered at grand mean
Age^2	The squared age of the child centered at grand mean
Usual Resident	Coded as 1 if the individual is a usual resident of the household and 0 if not
Child of Head	Coded as 1 if the individual is the child of the household head and 0 otherwise
Prop. of Children < 5	Proportion of household members who are less than 5 years old
Rural	Coded as 1 if the household is located in a rural area and 0 otherwise
Male Head	Coded as 1 if the household is headed by a man and 0 otherwise
Head 40 - 59 years	Coded as 1 if the household head is between the ages of 40 and 59 inclusive and 0 otherwise
Head 60 - 79 years	Coded as 1 if the household head is between the ages of 60 and 79 inclusive and 0 otherwise
Head $\geq$ 80 years	Coded as 1 if the household head is at least 80 years and 0 otherwise[4]
Middle Income	Coded as 1 if the household is middle income and 0 otherwise
High Income	Coded as 1 if the household is high income and 0 otherwise[5]
Head HIV+	Coded as 1 if household head is HIV+ and 0 if negative or unknown
Head HIV status unknown	Coded as 1 if household head's HIV status is unknown and 0 if head is either HIV+ or HIV-
Head Uneducated	Coded as 1 if household head is uneducated and 0 otherwise
	Cluster Level Contextual Variable
Cluster HIV Rate	The weighted HIV prevalence rates at the community level
	Country Level Contextual Variable
Country Enrollment Rate	The weighted Enrollment rates at the national level

Table 5: Variable Description

Community Enrollment	Burkina Faso	Cameroon	D.R. Congo	Ethiopia	Ghana	Guinea	Kenya	Lesotho	Liberia	Malawi	Mali	Niger	Senegal	Sierra Leone	Swaziland	Zambia	Zimbabwe
Mean	25.4629	69.9848	58.8845	43.7872	58.5878	45.7571	76.0471	70.7228	46.8559	76.2974	36.5628	32.3360	44.7868	62.6147	68.7392	66.5060	66.6448
Std. Dev.	20.5263	19.4949	17.8182	22.2725	18.1275	23.5128	15.7913	10.4968	20.6388	9.6688	22.7077	20.6259	23.2337	21.6637	17.2218	12.8698	12.8975
Median	20.2254	75	60.0585	44.7761	62.1820	46.1538	80	72.1576	48.7955	77.4194	35.1648	30.0794	46.0044	67.6471	72.2222	68.5185	68.1818
Obs	400	466	300	534	412	292	395	400	298	847	407	342	376	353	275	319	398

Table 6: Summary Statistics of Cluster Enrollment Rate (%)

Community Enrollment	Burkina Faso	Cameroon	D.R. Congo	Ethiopia	Ghana	Guinea	Kenya	Lesotho	Liberia	Malawi	Mali	Niger	Senegal	Sierra Leone	Swaziland	Zambia	Zimbabwe
Mean	1.8167	5.7832	1.3277	2.0049	2.2586	1.5534	7.0473	22.2591	1.6783	10.7839	1.2155	1.0425	0.8874	1.5185	26.8747	14.2148	18.0582
Std. Dev.	3.7134	7.0585	2.4655	4.1870	3.8330	3.2699	9.4101	12.6784	2.4476	11.6696	2.8586	2.8892	2.5364	3.5170	12.2443	10.2653	9.3527
Median	0	4.2834	0	0	0	0	4.6556	21.7038	0	7.84921	0	0	0	0	25.5852	13.5156	17.0611
Obs	400	466	300	535	412	292	395	400	298	847	407	342	376	353	275	319	398

Table 7: Summary Statistics of Cluster Prevalence Rate (%)