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Centre for Applied Microeconometrics

Department of Economics
University of Copenhagen

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Sibling Dependence, Uncertainty and Education:
Findings from Tanzania

Helene Bie Lilleør

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Helene Bie Lilleør[*]

CAM & Department of Economics

University of Copenhagen

and

Rockwool Foundation Research Unit

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Abstract

Primary school enrolment rates are continuously low in many developing countries. The main explanation in the economic literature on schooling is focused on credit constraints and child labour, implying that the indirect cost of schooling in terms of foregone earnings is too high. This paper investigates the effects of future income uncertainty on sibling dependence in the schooling decisions of rural households in developing countries. Schooling tends to direct skills towards future urban employment, whereas traditional rural education or on-farm learning-by-doing tends to direct skills towards future agricultural employment. Given this dichtomy, the question is then: Does future income uncertainty influence the joint educational choice made by parents on behalf of their children and is it possible to test this on simple cross-sectional data? I extend a simple human capital portfolio model to a three period setting. This allows me to explore the natural sequentiality in the schooling decision of older and younger siblings. The model can generate testable empirical implications, which can be taken to any standard cross-sectional data set. I find empirical evidence of negative sibling dependence in the educational decision, which is consistent with a human capital portfolio theory of risk diversification and which cannot be explained by sibling rivalry over scarce resources for credit constrained households. The paper thus provides a complementary explanation to why enrolment rates in developing countries are often continuously low.

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1 Introduction

Primary school enrolment rates are continuously low in many developing countries. The main explanation in the economic literature on schooling is focused on credit constraints and child labour, implying that the indirect cost of schooling in terms of foregone earnings is too high, see Edmonds (2007) and Lilleør (2008) for a detailed literature review. Government policies focusing on lowering the direct costs of schooling in terms of tuition fees, availability of books and uniforms might ameliorate the problem, but if high indirect costs are the main reason for low enrolment rates, such policies will not be enough to overcome the household budget constraint. In Sub-Saharan Africa, especially in rural areas where household-based production systems dominate the agricultural sector, the concept of foregone earnings of sending children to school becomes more vague and, more importantly, on-farm child work may itself be an essential component of traditional education, a possible alternative to formal schooling, as suggested by Rodgers and Standing (1981), Bekombo (1981), Grootaert and Kanbur (1995), and more recently and in more detail by Bock (2002). Furthermore, rural areas suffer from missing capital and pension markets, generating a need for informal insurance and savings mechanisms to shield consumption against income failure and secure old-age subsistence. Liquidity constraints and high foregone earnings of child labour may therefore not be the only explanations for low enrolment rates in primary schools.

In this paper, I argue that the rural-urban divide and uncertainty about future income of children, upon which parents rely for old-age security, combined with the fact that most children have siblings and parents are therefore likely to make a joint human capital investment decision regarding *all* their children, can make it optimal for parents to send some, but not all, of their children to school. Lack of schooling might therefore not only be due to cost side constraints in the human capital investment decision, but could also be due to uncertainties about the return side. However, the vast majority of papers on child labour and schooling focus on the cost side of the human capital investment decision (Edmonds (2007)), and on the role of child labour when households are exposed to transitory income shocks, e.g. Jacoby and Skoufias (1997), Jensen (2000) and Beegle, Dehejia, and Gatti (2006). This paper contributes to the existing literature by focusing on the uncertainty associated with the future returns of the human capital investment decision. The purpose being to complement the exisiting, and by all means valid, cost side explanations for child labour with an additional explanation that, given the empirical findings, sheds new light on the human capital investment decisions faced by parents in rural areas.

Most developing countries have a large agricultural sector and a somewhat smaller urban sector. There will always be uncertainty about future income in both of these sectors, but the uncertainties across sectors may largely be uncorrelated. As long as schooling tends to direct children towards future urban sector employment, and on-farm child work or learning-by-doing

is thought of as a traditional way of educating a child for future employment in the agricultural sector, then it can be shown that enough uncertainty about future income can prevent full school enrolment among siblings, even in a world with perfect credit markets. Missing capital markets can thus influence parental choice of schooling in two additional ways, apart from the standard credit constraint argument. First, income source diversification becomes an important means of income smoothing, as Morduch (1995) puts it, for households to minimise the risk of complete income failure both at present and in the future. Second, children play an important role of being old-age pension providers for their parents, since both private and public pension schemes are very limited. Future earnings and future income source diversification of children therefore become important for parents to secure their old-age subsistence.

Using a simple two-period human capital portfolio model for the joint educational decision of siblings, I show that future income uncertainty can indeed have a negative effect on the proportion of siblings in school. Model calibrations show that the negative effect can be surprisingly large even for moderate levels of uncertainty. Although model calibrations are based on simple data moments, the findings give some indications of the importance of uncertainty in the human capital investment decision. A logical extension would be to estimate the effect of future uncertainty on the actual proportion of children in school. However, it is, by definition, very difficult to get a good measure of future uncertainty, and thus virtually impossible to identify the actual effect of uncertainty on the optimal human capital portfolio of children in a household. An alternative is therefore to find other implications of the influence of future income uncertainty on the joint schooling decision which can be estimated in data and which cannot be caused by any other observationally equivalent explanations. One possibility is to take advantage of the natural sequentiality in schooling between younger and older siblings. The two-period model is therefore extended to a three-period model, which yields direct implications for the nature of sibling dependency caused by risk diversification and different from sibling dependency caused by sibling rivalry over scarce resources, as suggested by Morduch (2000). The three period model allows for younger and older cohorts of siblings and analyses the effect of schooling of the older cohort on the younger one. Lack of schooling due to child labour or credit constraints result in a positive relationship between the schooling of the older and younger siblings, because the older cohort generate income when the school fees of the younger cohort have to be paid. However, lack of schooling due to risk diversification result in a negative relationship between the older and younger cohorts within a household, even when credit markets are perfect. Calibrating, and partly simulating, the three period model yields testable empirical implications, which can be taken to standard cross-sectional data set without any requirements about only observing households with completed fertility and completed schooling among their children.

Based on a nation-wide large scale cross-sectional household survey undertaken in Tanzania

in 1994, I find evidence of sibling dependency consistent with risk diversification having a strong influence on the joint human capital investment decision of sons, but not of daughters. Results are considerably stronger among rural households compared to urban households. These results are consistent with the fact that most societies in Tanzania are patrilineal and therefore only sons are of importance for old-age security, and with the fact that only rural households have a credible option of educating their children traditionally through on-farm learning by doing. Sibling dependence in the schooling decision might therefore not only be caused by sibling rivalry for scarce resources, but can also be due to a need for risk management by diversifying future income sources. This has direct implications for educational policies, since lack of enrolment might not only be a matter of costs of schooling, but also of content in terms of a relevant curricula for future employment in the agricultural sector. In fact, when questioned about which subjects should be taught in primary schools, parents invariably allocate top rank to a course in 'technical skills for agriculture and business', indicating a demand for skills diversification in formal education.

In section 2 the theoretical framework is outlined describing both the two-period model and the three-period extension as well as the results of the model calibrations. Data is described in section 3, whereas section 4 has a description of the empirical specification used for estimation, and the empirical results are analysed and discussed. Section 5 concludes.

2 Theoretical Framework

The model developed in this section differs from most of the models in the existing literature in two ways. First, the model is not a one parent-one child model of human capital investment, but rather a one parent-N children model thus allowing for dependency among siblings in the joint human capital investment decisions of the parents. Second, the model introduces future income uncertainty, which means uncertainty about the returns to education. A matter which, despite the importance for the investment decision, has largely been ignored in the literature[1]. The two period model is a direct replication of the two period model in Lilleør (2008). The contribution of this paper is the extension to a three period model, which generates testable empirical predictions that can be taken directly to any standard cross sectional data set.

In the following section, the basic two-period model set-up gives a general understanding of how uncertainty can affect the human capital investment allocation. The model is calibrated using information from a nationwide large-scale household survey in Tanzania in section 2.2. The three period model is laid out in section 2.3 and calibration results are described in section 2.4.

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[1]Two exceptions are recent papers by Pouliot (2005) and by Estevan and Baland (2007)

2.1 The basic two-period model

The model is a two period unitary household model, where parents function as a unified sole decision maker. There is no discounting of the future and no interest rate on savings or credit. In the first period, parents earn agricultural income Y_1, which they allocate between first period household consumption c_1, savings s, and the education expenses for their N children. N is assumed to be exogenously given, since the emphasis here is not on the effect of uncertainty on fertility decisions, but on the effect of uncertainty on the joint human capital investment decision of children, given the fertility of the household.[2]

There are two types of education in the model, general formal education achieved through primary schooling and specific traditional education achieved through on-farm learning-by-doing. Traditional education directs children towards future employment in the agricultural sector (a), whereas formal education directs children towards future employment in the non-agricultural urban sector (b) in the second period. Parents thus face a discrete choice for each of the N children of whether he or she should be educated traditionally or formally. A child can only receive one type of education[3]. In the second period, traditionally educated children earn agricultural income, y_2^a , whereas formally educated children earn urban income, y_2^b. Second period income of children in the agricultural sector will be a function of the first period parental income under the assumption that children will be working in similar agricultural production systems as their parents, and parents transfer specific human capital skills to their children as part of their traditional education. Thus $y_2^a = f(Y_1), f'(Y_1) > 0$.

Parents do not generate any income in the second period, but rely fully on their savings and the joint agricultural and urban income transfers from their N children for second period household consumption, c_2. Second period income is uncertain. Parents therefore maximise a joint von Neuman-Morgenstern expected utility function defined over and separable in household consumption, c_t, where $t = 1, 2$. The utility function is assumed to be concave, such that $U'(c) > 0$ and $U''(c) < 0$. The household solves the following maximisation problem

$$\max_{\pi,s} EW(c_1, c_2) = U(c_1) + EU(c_2) \tag{1}$$

subject to the budget constraints for period 1 and period 2, respectively

$$
\begin{aligned}
c_1 &= Y_1 - (1-\pi)Ne^a - \pi Ne^b - s \\
c_2 &= N^{-\alpha}((1-\pi)Ny_2^a + \pi Ny_2^b) + s
\end{aligned}
\tag{2}
$$

---

[2]It is conceivable that the fertility decision and the human capital investment decision of the born and unborn children are both influenced by the parents' preference for old-age security, which suggests modelling the two decisions jointly. However, to keep things simple, I focus on the effect of future income uncertainty on the human capital investment decision of children conditional on the household having completed their fertility.

[3]This is a simplifying assumption. The choice here is not on how many hours a child spends in school or working, but rather whether he or she graduates with full primary school education or not.

where π is the proportion of children, which parents have chosen to educate formally through schooling. That is, π is the portfolio allocation of children between traditional and formal human capital investments. The number of children who receive schooling in the first period is thus given by πN and the number who are educated within the traditional agricultural based system is $(1-\pi)N$.[4] The total amount of educational expenses is $(1-\pi)Ne^a + \pi Ne^b$, where e^a is the educational expenditure for each child in traditional education, e.g. supervisional costs of parents, and e^b is the educational expenditure for each child in formal education, e.g. tuition fees and uniform costs. Educational expenditures are allowed to differ over the two sectors, and they are considered both non-negative.[5]

Savings can be negative, and both the discount rate and the interest rate are normalised to unity and are thus explicitly left out of the model for simplicity. By assuming perfect credit markets, I can ignore any effect of liquidity constraints on the schooling decision and thus focus on the effect of future income uncertainty on the joint human capital portfolio decision of all N children in the household. The question is: can this alone result in less than full school enrolment among siblings, i.e. a model prediction of $\pi < 1$ solely due to uncertainty.

Second period consumption will equal any capital transfers from period one in terms of savings or dissavings, s plus a fraction, $1/N^\alpha$, of total income of all children, which is given by the income of children in the agricultural sector $(1-\pi)Ny_2^a$, and the income of children in the urban sector πNy_2^b. Children are thus assumed to transfer a certain fraction of their income to their parents. The fraction is the same for all children, irrespective of their sector of employment, but it depends on their number of siblings for $\alpha > 0$. In principle, $\alpha \in [0;1]$, but in the following I will assume that $\alpha \in]0;1[$ to ensure that there is a positive, but diminishing marginal effect of having more children on second period income. When $\alpha = 0$, children share all their income with their parents. When $\alpha = 1$ children share only a fraction $1/N$ of their income with their parents, resulting in parents receiving the equivalent of one full income from their children in total. If there is only one child in the household that child will be the sole breadwinner of the family in the second period and is forced to share his/her full income with the parents, irrespective of the size of α.

Parents are faced with two choice variables; how much to save or dissave s, and which proportion of their children to educate formally through schooling π. The first order condition with respect to s is

$$U'(c_1) = EU'(c_2) \tag{3}$$

---

[4] For analytical simplicity, π is written as continuous in the theoretical model, but it will be treated as discrete in the calibrations and in the empirical model.

[5] While the literature on child labour and schooling generally set e^a as negative and thus as a source of income, I here follow Bock (2002) in stating that the overall learning potential in the tasks completed by children in agriculture is higher than the immediate return. If children were only undertaking tasks with no learning, but high immediate output, such as fetching water or firewoods, there would be no transfer of farm-specific human capital from parents to children and therefore no future agricultural return from such activities.

That is, savings s will be chosen such that marginal utility in period one equals the expected marginal utility of period two. The first order condition with respect to π is given by equation (4), where π^* is the optimal solution for the maximisation problem above

$$
\begin{array}{rcll}
N(e^b - e^a)U'(c_1) & = & E[N^{1-\alpha}(y_2^b - y_2^a)U'(c_2)], & \text{for } 0 < \pi^* < 1 \\
N(e^b - e^a)U'(c_1) & > & E[N^{1-\alpha}(y_2^b - y_2^a)U'(c_2)], & \text{for } \pi^* = 0 \\
N(e^b - e^a)U'(c_1) & < & E[N^{1-\alpha}(y_2^b - y_2^a)U'(c_2)], & \text{for } \pi^* = 1
\end{array}
\tag{4}
$$

where

$$
E[N^{1-\alpha}(y_2^b - y_2^a)U'(c_2)] = E(N^{1-\alpha}(y_2^b - y_2^a))EU'(c_2) + cov(N^{1-\alpha}y_2^b, U'(c_2)) - cov(N^{1-\alpha}y_2^a, U'(c_2))
$$

Uncertainty about second period income results in two covariance terms, both negative, between the second period income variables, y_2^a and y_2^b, and marginal utility, $U'(c_2)$. These terms will, when they are strong enough, pull the optimal portfolio allocation, π^* away from each of the two corner solutions. Uncertainty in the agricultural sector will have a positive effect on π^* because it will increase the right hand side of the first order consition for π and pull towards the $\pi^* = 1$ corner solution. Uncertainty in the urban sector, on the other hand, will have a negative effect on π^* because it will decrease the right hand side of the the first order condition for π and thus pull towards the $\pi^* = 0$ corner solution.

In the following, I assume that there is no covariant uncertainty between second period income from children in the urban sector and children in the agricultural sector. This allows me to simplify the problem by normalising uncertainty about income from the agricultural sector to zero, and thus solely focus on the effect of uncertainty of urban income on the optimal proportion of children in formal schooling. Going back to the first order condition for π, equation (4), this means concentrating on the covariance term, which can reduce the right-hand side of the first order condition and thus reduce the optimal π^*. That is, focusing on the somewhat more relevant question of what can result in an optimal π^* below 1, rather than what can result in an optimal π^* above 0.

This is not to say that there is no uncertainty in the agricultural sector, but rather that uncertainty associated with income transfers from distant migrant children in the urban sector is higher. These migrant children may face higher income levels, but also relatively more variation, since the urban labour market entails a risk of unemployment, which is not present among subsistence farmers in the agricultural sector. Furthermore, parents may also perceive the size and the frequency of income transfers from urban migrant children to be more uncertain compared to the daily support and in-kind assistance from home children engaged in local agricultural sector[6].

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[6]The uncertainty could thus also, in effect, be an intergenerational agency problem between parents and

The uncertainty, that parents face about income transfers from migrant children in the urban sector is modelled as a simple mean-preserving spread. Each migrant child can either get a good (typically formal sector) job or not, where the probability of a good draw in the urban labour market is given by $p = 0.5$. Migrant children in good jobs have an urban income of $y_2^b = \mu + \varepsilon$, whereas migrant children without good jobs have an urban income of $y_2^b = \mu - \varepsilon$.[7] This means that second period urban income is given by

$$y_2^b = \begin{cases} \mu + \varepsilon & \text{w.p.} \quad p = 0.5 \\ \mu - \varepsilon & \text{w.p.} \quad (1-p) = 0.5 \end{cases}$$

The mean and the variance for each child in the urban sector is $E(y_2^b) = \mu$ and $Var(y_2^b) = \varepsilon^2$. Given this specification of uncertainty, the first order condition for π rewrites (4) as

$$N(e^b - e^a)U'(c_1) = N^{1-\alpha}(\mu - y_2^a)EU'(c_2) + cov[N^{1-\alpha}y_2^b, U'(c_2)] - 0$$

where the specification of the covariance term will depend on the degree of risk correlation in the urban labour market outcome. The expected total income transfers from all the πN children, which have gone to the urban sector, is simply $E(\pi N^{1-\alpha}y_2^b) = \pi N^{1-\alpha}\mu$, independent of the degree of risk correlation among migrant siblings. But the variance of their expected total income, $Var(\pi N^{1-\alpha}y_2^b)$ and the covariance above, $cov(N^{1-\alpha}y_2^b, U'(c_2))$ will both depend on the degree of risk correlation in urban income.

I consider the two extremes where income transfers from siblings in urban employment are either perfectly correlated or uncorrelated. Reality is likely to lie somewhere in between. When there is perfect risk correlation among siblings in urban employment, all siblings will either have a good draw and then their income transfers will amount to $\pi N^{1-\alpha}(\mu + \varepsilon)$, or they will all have a bad draw and then their income transfers will amount to $\pi N^{1-\alpha}(\mu - \varepsilon)$, hence the variance is $Var(\pi N^{1-\alpha}y_2^b) = \pi^2 N^{2-2\alpha}\varepsilon^2$. When there is no risk correlation among siblings, they all face the same urban labour market lottery irrespective of the labour market outcomes of their siblings. The variance under no risk correlation is thus smaller and depends on the binomial coefficient $\binom{\pi N}{i}$, where i denotes the number of successful siblings in the urban labour market (i.e. those where $y_2^b = \mu + \varepsilon$) and πN is the total number of siblings in the urban sector in the second period, $Var(\pi N^{1-\alpha}y_2^b) = N^{-\alpha}\sum_{i=0}^{\pi N}\binom{\pi N}{i}\frac{1}{2^{\pi N}}(i\varepsilon - (\pi N - i)\varepsilon)^2 = \pi N^{1-\alpha}\varepsilon^2$.

As long as uncertainty in the agricultural sector and the urban sector do not covary, households will have an incentive to diversify their human capital investments to reduce future risk exposure. For a given set of preferences, it can be shown that, once the optimal choice of π^* and s^* have been found by solving the two first order conditions, the derivative of π^* with respect to ε is negative. If the need for diversification is strong enough, that is if ε is large enough, it will have a negative impact on the proportion of children sent to school in the optimal human capital portfolio of the household.

2.2 Calibrations

Although it is possible to show analytically, that the partial derivative of π^* with respect to ε is negative. This does not indicate whether existing levels of uncertainty in urban income alone can result in less than full enrolment. Only by calibrating the model, using actual levels of school expenditures and income in both the agricultural and urban sector, is it possible to determine whether the actual dispersion in urban income, $Var(y_2^b) = \varepsilon^2$, could potentially keep some children out of school purely due to future income or risk diversification, even under perfect credit markets.

The model is calibrated for the average household using simple data moments based on the table of summary statistics (table 1 in section 3), and constant relative risk aversion preferences with a risk aversion parameter of $\rho = 2$.[8] Rural and urban income are proxied by rural and urban household expenditure measures of 0.707 and 1.247 USD, respectively. First period parental income and second period agricultural income are normalised to unity $Y_1 = y_2^a = 1$, the spread of second period agricultural income is normalised to zero, and second period urban income and spread are adjusted accordingly, resulting in $y_2^b = 1.26/0.708 = 1.780$ and $\varepsilon = (1.218 - 0.501)/0.708 = 1.013$. Schooling expenditures (e^b), including annual uniform expenses, amount to 2.5 per cent of parental income, expenses associated with educating the children traditionally are simply set at half, i.e. $e^a = 0.0125$.[9]

Figure 1 shows the pure effect of future urban income uncertainty ε on the optimal proportion of siblings educated formally π^* for $N = 1, 3, 5$, and 7 children, respectively[10]. The discrete jumps in the graph stem from the discrete number of children. For instance, when $\varepsilon \in [1.1; 1.6]$ a household with three children (green line) will only be sending one out of the three to school under perfect correlation in ε's. On average, the sample of households have 5-6 children in rural areas.

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[8]For additional calibration results on the two-period model, please refer to Lilleør (2008).

[9]The parameter values differ from those of Lilleør (2008) because a different and smaller sample is used. I only include households which have both children of school age and children beyond school age in order to resemble the three period model as closely as possible. However, this does not change the qualitative findings of the calibrations.

[10]For a simpler version of figure 1, refer to figure 0 in Lilleør (2008).

(Figure 1)

It is clear from figure 1 that future uncertainty, the level of which is proxied by actual levels of income spread, can indeed result in households diversifying their human capital investments. For the average household with five children, an $\varepsilon = 1$ (which corresponds to the standard deviation of the average income level in data) results in a predicted interval of π^* of $[0.6; 1]$ and likewise the actual enrolment rate of $\pi^* = 0.7$ corresponds to an optimal human capital portfolio when future urban income uncertainty is in the interval of $\varepsilon = [0.9; 1.7]$. Both intervals include the observed values in the data. These are the predictions based on a model of perfect credit markets, the less than full school enrolment is thus purely a result of risk diversification and not in any way driven by sibling rivalry over resources. Adding credit constraints ($s \geq 0$) and child labour ($e^a = -0.025$) to the calibrations shift the graphs inwards towards the origin, resulting in even lower optimal levels of π^*, see figure 2. Now the actual enrolment rate of $\pi^* = 0.7$ corresponds to an interval of uncertainty of $\varepsilon = [0.3; 1.2]$. Without uncertainty ($\varepsilon = 0$), the model predicts that the optimal schooling rate for households with five children is 0.8, which is slightly above the actual enrolment rates. This enrolment rate is a pure effect of sibling rivalry in the constrained household, but any further reduction due to uncertainty ($\varepsilon > 0$) is an effect of sibling portfolio dependence in the need for risk diversification.

(Figure 2)

From these two figures it is difficult to determine whether sibling dependence is primarily caused by sibling rivalry over scarce resources or by the need to diversify future income sources and their associated risk. Both explanations can generate model predictions consistent with simple data moments and the two effects are likely to co-exist. The point of this exercise is not to question the importance of liquidity constraints and scarcity of resources in the human capital investment decisions of the household, but to emphasise that liquidity constraints and child labour might not be the full explanation for lack of schooling.

2.3 A Three Period Model

The two-period model is appealing for its simplicity, the negative effect of future income uncertainty on the human capital portfolio decision of the parents is immediate. Unfortunately, the model does not lend itself very easily to cross sectional data or even standard panel data, because the time span would be too short to cover the two periods in question. However, one of the key aspects of the model is the prediction that households will tend to diversify future income sources if there is enough uncertainty about future income. This need for diversification can spill over into the schooling choice today and create potential for a negative sibling dependence in schooling; a negative dependence, which is not generated by constraint effects

due to sibling rivalry for currently scarce resources, but purely driven by the need for risk diversification in the human capital portfolio of siblings. The challenge then becomes to test for negative sibling depence in schooling without implicitly testing for a liquidity constraint.

This can be done by exploring the natural sequentiality in the schooling decision of siblings and looking at two different cohorts of siblings within a household. The older cohort, who have completed schooling will be generating income and is therefore able to contribute resources to the household rather than demand them. That is, all else equal, households with older economically active siblings will have less of a binding liquidity constraint than households without. This in itself should have a positive effect on schooling if households are liquidity constrained. On the other hand, if the proportion of formally educated older siblings is higher than the optimal overall proportion of formally educated children in the household π^*, then this is likely to have a negative effect on the proportion of formally educated younger siblings for the desired future income source diversification to be achieved.

By extending the model to a three period model, it becomes possible to analyse how exactly the portfolio allocation of the older siblings should affect the portfolio allocation of the younger ones. This will have direct empirical implications, which can be tested in the cross sectional data as long as there are enough households with children both of and beyond school age. The three period model is set up such that older siblings are educated in the first period and work in the second and third period. Younger siblings are educated in the second period and only work in the third period. Parents generate income in the first and the second period, but not in the third period, where they have reached old age and rely fully on the income of their children. The human capital investment decision now becomes sequential. There will still be an optimal overall π^* for the parents, which depends on the degree of uncertainty about future income, here isolated in the urban sector. The sequentiality will generate predictions of how the proportion of formally educated siblings from the first cohort, π_1^* will affect the proportion of formally educated siblings from the second cohort, π_2^* such that the overall optimal π^* is achieved. The total number of children N as well as the allocation of children between the two cohorts, N_1 and N_2 are all exogenous.

In period 1, parents face uncertainty about period 2 and 3 and maximise the following expected utility function

$$\max_{\pi_1, \pi_2, s_1, s_2} EW(c_1, c_2, c_3) = U(C_1) + EU(c_2) + EU(c_3)$$

11

subject to the budget constraints for the three periods

$$
\begin{aligned}
c_1 &= Y_1 - (1 - \pi_1)N_1 e^a - \pi_1 N_1 e^b - s_1 \\
c_2 &= Y_2 + N_1^{-\alpha_2}[(1 - \pi_1)N_1 y_{12}^a + \pi_1 N_1 y_{12}^b] - (1 - \pi_2)N_2 e^a - \pi_2 N_2 e^b + s_1 - s_2 \\
c_3 &= N^{-\alpha_3}[((1 - \pi_1)N_1 + (1 - \pi_2)N_2)y_3^a + \pi_1 N_1 y_{13}^b + \pi_2 N_2 E y_{23}^b] + s_2
\end{aligned}
$$

N_1 is the size of the first and older cohort of siblings, π_1 is the proportion of these that are educated formally. Their second period urban income is y_{12}^b, which has a mean preserving spread of ε_{12}, and their third period urban income is y_{13}^b with a mean preserving spread of ε_{13}. N_2 is the size of the second and younger cohort of siblings. π_2 is the proportion of these that are educated formally, and their third period urban income is y_{23}^b with a mean preserving spread of ε_{23}. The total number of children is $N = N_1 + N_2$. The assumptions from the two period model are maintained. I do, however, allow for different degrees of income transfers in period 2 and period 3, such that $\alpha_2 < \alpha_3$. This is to mimic the fact that only in old-age are parents dependend on their children for subsistence, as well as the fact that older siblings in period 2 will primarily be of an age where they are about to establish their own households and therefore may not contribute as much to the parental household as in the future.

The key point of interest, in terms of empirical implications, is the relationship between π_2 on π_1. This relation is immediate if the system is solved backwards in time, that is solving the maximisation problem in period 2, taking the outcome of period 1 as given. The maximisation problem therefore simplifies to the following

$$
\max_{\pi_2, s_2} EW(c_2, c_3) = U(c_2) + EU(c_3)
$$

subject to

$$
\begin{aligned}
c_2 &= Y_2 + N_1^{-\alpha_2}[(1 - \pi_1)N_1 y_2^a + \pi_1 N_1 y_{12}^b] - (1 - \pi_2)N_2 e^a - \pi_2 N_2 e^b + s_1 - s_2 \\
c_3 &= N^{-\alpha_3}[((1 - \pi_1)N_1 + (1 - \pi_2)N_2)y_3^a + \pi_1 N_1 y_{13}^b + \pi_2 N_2 y_{23}^b] + s_2
\end{aligned}
$$

which, under the assumption of no liquidity constraints, yields two first order conditions for π_2 and s_2, respectively.

$$
\begin{aligned}
N_2(e^b - e^a)U'(c_2) &= E\left[N^{-\alpha_3}N_2(y_{23}^b - y_3^a)U'(c_3)\right] \\
U'(c_2) &= EU'(c_3)
\end{aligned}
$$

It is possible to find the derivative of π_2 with respect to π_1 without specifying the preference or uncertainty structure by differentiating the system above and using Cramer's rule. Although

not perfectly unambiguous analytically, it turns out that under no liquidity constraints and no child labour and with enough uncertainty, the derivate $d\pi_2/d\pi_1$ is negative. Whereas if liquidity constraints are imposed, child labour is introduced and uncertainty is virtually nil, then the derivative $d\pi_2/d\pi_1$ is positive. See appendix A1 for the exact specification.

2.4 Calibrations and Simulations

Before turning to the empirical analysis, the qualitative results in terms of the $d\pi_2/d\pi_1$ derivative are verified numerically. The second period maximisation problem of the three period model is therefore calibrated under a set of different uncertainty structures in the three urban income measures y_{12}^b, y_{13}^b and y_{23}^b. Uncertainty is still modelled as a mean preserving spread for the urban sector and normalised to zero in the agricultural sector. However, now the uncertainty measures, (ε_{12}, ε_{13} and ε_{23}) can be perfectly correlated or uncorrelated within cohort, between cohorts and over time. This gives rise to a variety of different combinations of uncertainty structures. In the following graphs, I have assumed that uncertainty is uncorrelated over time ($\varepsilon_{12} \neq \varepsilon_{13}$), but perfectly correlated within and between sibling cohorts ($\varepsilon_{23} = \varepsilon_{13}$). This is entirely for illustrative purposes. Calibrations are done for all the possible combinations of uncertainty structures and the overall qualitative results are the same.

Due to the perfect correlation within cohorts, period 2 can either be in a high income state ($y_{12} = \mu + \varepsilon_{12}$) or in a low income state ($y_{12} = \mu - \varepsilon_{12}$), depending on the urban labour market outcomes for the $\pi_1 N_1$ children in the urban sector. The model is calibrated for $N_1 = 3, N_2 = 3, \alpha_2 = 1.5, \alpha_3 = 0.95$ and $y_2 = 0.5$, the remaining values are identical to the calibration of the two period model above. Parental second period income has been reduced to ensure that the sum of parental income and the income transfers from the oldest cohort are in the neighbourhood of 1, the normalised agricultural income. E.g. if all N_1 are traditionally educated and earn $y_2^a = 1$, the total income of the household in the second period is $0.5 + 3/3^{1.5} = 1.0774$. Argueably, this is a bit arbitrary, but the qualitive results are robust to different specifications. What is important is to have some degree of binding liquidity constraints under no credit markets.

In figure 3 the negative relationship between schooling of the older and younger cohort is very clear. The left panel shows the relationship when the second period urban outcome for cohort one is high, the right panel when the second period urban outcome is low. It is clear, that there is only a negative relationshipbetween π_1 and π_2 if there is enough uncertainty. For uncertainty levels below the normalised agricultural income ($\varepsilon < 1$) households will always be educating all children in the younger cohort irrespective of the older cohort. The need for risk diversification is not strong enough to generate any sibling dependence. Each line represents a different degree of uncertainty (ε) and thus different optimal overall π^* from the two period problem. Heterogeneity across households, in terms of the uncertainty level they are facing, will

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generate a variety of different optimal π^*'s and thus different optimal (π_1, π_2) combinations.

(Figure 3)

Take the purple line ($\varepsilon = 1$) in the right panel above as an example. Here the optimal overall $\pi^* = \frac{1}{2}$, or 3 out of 6 children are being sent to school. When $\pi_1 = 1$ all three older siblings are sent to school and therefore none of the younger ones are in school, and vice versa. If uncertainty increases ($\varepsilon \in [1.25; 1.75]$), this depresses the overall optimal π^* to $1/6th$ and only one out of the total of six children are sent to school such that either $\pi_1 = 1/3$ or $\pi_2 = 1/3$ (blue dotted line). The negative relationship between π_1 and π_2 is thus purely mechanical in the sense that it is fully determined by the overall optimal π^* and it only exists for $\pi^* > 0$ and $\pi^* < 1$. When $\pi^* = 0, \pi_1 = \pi_2 = 0$ and when $\pi^* = 1, \pi_1 = \pi_2 = 1$.

The possible heterogeneity in π^* results in a cross sectional relationship between π_1 and π_2 which is not strictly negative. This can be shown by simulating a distribution for π^* and π_1 and from these generate π_2. Overall it must hold that $\pi^* = (\pi_1 N_1 + \pi_2 N_2)/N$ such that $\pi_2 = (\pi^* N - \pi_1 N_1)/N_2$. From this, the mechanical negative relationship between π_1 and π_2 is obvious. The simulations are very simple and do not incorporate the model as such. The main point is simply to show the negative relationship between π_1 and π_2 as a consequence of $\pi^* < 1$ due to a need for risk diversification. To ensure a discrete nature in the overall optimal π^*, it is generated as n^b/N, where n^b is the optimal number of children with schooling out of the total number of N children. N is drawn from a Poisson distribution with $E(N) = 5.6$ as in the data. n^b is drawn from a binomial distribution given N and with probability $E(\pi) = 0.715$ as in the data, see table 1 in section 3. From the simulation results in figure 4, it can be seen that if the distribution of π^* covers the full range between 0 and 1, then a least squares estimation of the cross sectional relationship between π_1 and π_2 results in an inverse U relationship.

(Figure 4)

The correpsonding graph based on the actual data for π_1 and π_2 without any restrictions on π^* is given below in figure 5. Eyeballing the two figures, they seem very close. A joint test of equality of regression coefficients for the two π_1 terms in the least squares regression cannot be rejected.

(Figure 5)

Comparing figure 4 and figure 5, it shows that the simulated conditional mean function from a very simple version of the model (where the only role of uncertainty is to make $\pi^* < 1$) gives exactly the relationship seen in the data.

The obvious question is then, what else (other than uncertainty and the need for risk diversification) could result in an optimal overall $\pi^* < 1$, which would generate the same relationship

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between π_1 and π_2. Liquidity constraints and child labour cannot, I will return to this shortly. Another possibilty is that heterogenity in π^* is driven by heterogeneity in ability (in terms of schooling) across or within households. If there is heterogenity in ability *across* households but not within households, such that each household sample from an ability distribution and all children within households are identical, then the overall π^* for each household will always be at a corner. There will thus be a bang–bang solution in the sense that for the low ability household $\pi^* = 0$ (for these returns to traditional eduaction will be higher than the returns to formal education), and for high ability households $\pi^* = 1$ (for these schooling is the most profitable educational choice). This is a consequence of no uncertainty and no liquidity constraints.

On the other hand, if the optimal overall $\pi^* < 1$ due to heterogeneity *within* households, such that schooling is only a profitable investment for some children, then this will yield the same predictions in figure 4 as uncertainty. Thus, I cannot distinguish the effect on π^* of within household ability differences from uncertainty and the need for risk diversification. However, it must be said that for within household ability differences to be generating the same results, the dispersion in ability within households must be large enough to locate some siblings below the cut off point where schooling is no longer the most profitable educational choice, and other siblings above.

Although liquidity constraints can result in less than full enrolment among siblings within a household, they can never actually general an optimal $\pi^* < 1$. For liquidity constained households, the optimal π^* always equals unity as long as schooling is the most profitable educational choice, but the household is forced into a second best solution because it is not able to optimize intertemporarily. For such households, the choice of π_1 will affect the choice of π_2. Even if the household was not able to achieve $\pi_1 = 1$ due to liquidity constraints, higher π_1 will result in higher second period income and, all else equal, this will ameliorate the liquidity constraint when it comes to educating the younger cohort. That is, there will be a positive relationship between π_1 and π_2. The simulations in figure 4 are based on an underlying relationship between π_1 and π_2 as illustrated in figure 3, however when introducing liquidity constraints and child labour the relationship between π_1 and π_2 is completely different, see figure 6.

(Figure 6)

In figure 6 it is clear that when there is no uncertainty ($\varepsilon = 0$), but child labour and liquidity constraints ($e^a = -0.025, s = 0$), the relationship between π_1 and π_2 is positive under high second period outcome for $\pi_1 N_1$ urban migrants and zero under low second period outcome. The positive effect under high second period outcome shows exactly the proposed effect of the second period income of the older cohort ameliorating the liquidity constraint in the human capital investment decision for the younger cohort.

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Any negative relationship between π_1 and π_2 in the data will thus be due human capital diversification, either as a consequence of uncertainty and the need for risk diversification or simply due to within household ability differences. It can not be generated by liquidity constraints and child labour. There are two other, equally important, implications of the human capital portfolio model. If $\pi^* < 1$ due to risk diversification of future income sources, then the negative sibling dependence should in principle only hold for rural households, because urban households do not have the agricultural income diversification possibility. Second, the portfolio effect should also only hold for sons and not for daughters, because Tanzania is largely a patrilineal society where the obligations of daughters vis-a-vis their family shift to their husband's family upon marriage. Daughters can therefore not be relied upon for old-age security and, thus, there is no need for ensuring risk diversification of their future income sources. Within household ability differences can not generate such predictions. There are no reasons to believe that within household ability heterogenity is gender specific, nor that only rural households should face within household ability differences, but urban households should not. Testing for differences across gender and across sector is therefore an implicit test of the uncertainty explanation versus the within household ability explanation.

3   Data

In order to test the empirical implications of the portfolio model above, I use a large-scale nationwide cross-sectional household survey from Tanzania undertaken in 1994, the Human Resource and Development Survey (HRDS).[11] It is a nationally representative survey of 5,000 households out of which more than half of the households have school-aged children. The HRDS data contains detailed information on individual household members, including their educational status. At household level, there is information about sources of income, detailed assets and expenditure information and, not least, schooling expenditures, school distance as well as the head's assesment of the quality of the local primary school. Out of the 5000 households, only households where the household head has children (or step-children) of school age as well as children beyond school age are included. Combined with a need for non-missing observations of the included variables, this reduces the sample to 1328 households, out of which slightly more than half are urban. Although the portfolio model is only applicable to rural households with access to both formal and traditional education, urban households are included for that exact comparison. Table 1 lists summary statistics for all relevant variables from the data set.

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[11] The survey was a joint effort undertaken by the Department of Economics of the University of Dar es Salaam, the Government of Tanzania, and the World Bank, and was funded by the World Bank, the Government of Japan, and the British Overseas Development Agency. For more information or access to the data see www.worldbank.org/lsms

[Table 1]

There are three groups of variables, which are included in the emprirical analysis. First of all, the sibling composition and allocation between formal education and traditional education. N_1 children are all children beyond school age, N_2 children are of school age that is between 7-17 years old. π_1 and π_2 refer to the proportion of children which are through or in formal schooling, respectively. The variables are also split by gender, allowing to test the hypothesised sibling dependence separately for sons and daughters. There is an average of 5-6 children in total, the number is slightly higher in rural than in urban areas. There is an overall schooling rate of children of slightly more than 70% for this sample of households.

The second group of variables characterise the household. These variable include proxies for model variables. Parental income is proxied by household expenditure. There are no income measures in the data set, and commonly expenditure measures are thought to be better proxies for life time income and less prone to measurement error than income measures, especially when looking at rural households with a family-based agricultural production system, Deaton (1998). More than 90 per cent of rural households have agriculture as their main source of income, whereas this number is almost 35 per cent for urban households, indicating that the rural urban divide in terms of agriculture and non-agriculture is not perfect, but still useful. Schooling is almost three times more expensive in urban areas, compared to rural areas, where the annual school costs amount to roughly 6 USD and rural school children have an average of 1.5 km to cover to go to school. 40 per cent of rural households have at least 2 heads of livestock or 5 pigs or sheep. Each rural household has an average of almost 15 hectars of land, but there is a lot of dispersion in this number. The median rural household has 10 hectars and only the top quartile of the distribution have land holdings above 18 hectars. There is a fairly even distribution of muslims, catholic and protestants in rural areas, whereas muslims are a dominating group in urban areas. There are more than 100 different tribes in Tanzania, in the empirical analysis below I control for tribal affiliation of the largest ten tribes at village level. Although income sources are clearly predominantly agricultural in rural areas, there are still roughly 20 per cent of households with wage or self-employment business income. This number is naturally considerably higher in urban area.

The last group of variables are indicator variables for whether the household head considers the local primary school to have an adequate or good quality of the variable in question. In general, school quality does not seem to be rated too poorly, except for school supplies.

4 Empirical Specification and Results

The proportion of children enrolled in school is the choice variable in the second period of the three period model above and thus also the dependent variable in the empirical analysis

below. It can be expressed either as the number of children attending school, n_2^b, out of the total number of school-aged children, N_2, or as the proportion, $\pi_2 = n_2^b/N_2$. This gives rise to two alternative empirical model specifications, either a double censored Tobit model or a binomial count model. The doubled-censored Tobit model can estimate the proportion of N_2 children in school, π_2 taking into account that π_2 is censored at 0 and at 1. However, π_2 will be of a discrete character since there is a natural upper bound to the total number of young offspring in a household. The underlying assumption of continuity in the dependent variable of the Tobit model might therefore be inappropriate.

The alternative is to model the choice of n_2^b directly as a count variable. It is then important to use a count model, which takes the upper censoring into account, such that predicted values of n_2^b never exceeds N_2. This is the key feature of the standard binomial count model, Winkelman (1997). This model estimates the number of children attending primary school n_2^b, conditional on the total number of school-aged children in the household N_2.[12] When conditioning on N_2, it is clearly treated as exogenous to the schooling decision and all results should be interpreted given the number of school aged children. Although the main empirical analysis is based on the binomial count model, results are also reported for the Tobit model as well as the linear probability model in section 4.2 to check whether results are robust to model specification.

4.1 Econometric Model

The number of children in school n_2^b is assumed to be binomially distributed and can therefore be thought of as a sum of independent and homogenous Bernoulli-trials up until N_2. That is, the current household demand for schooling is modelled as a sum of N_2 binary individual choices concerning school attendance, which are assumed to be independent and with the same school attendance probabilities $(\pi_2)^{13}$.

$$\Pr(school_i = 1) = \pi_2, \qquad \text{where } i = 1, 2, ..., N_2 \text{ and } \pi_2 \in [0; 1]$$

and n_b is binomially distributed

$$\sum_{i=1}^{N_2} school_i = n_2^b \sim Bin(N_2, \pi_2)$$

The expected value of n_2^b is $E(n_2^b) = N_2\pi_2$ and the variance is $Var(n_2^b) = N_2\pi_2(1 - \pi_2)$. The effect of different explanatory variables contained in **x** will enter through the link function

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[12] This model is not commonly used in the economics litearture, but a related example is by Thomas, Strauss, and Henriques (1990). They use the binomial model to study child mortality within families, conditional on the total number of children ever born.

[13] The assumptions of homogeneity and independence among children within the household will be relaxed shortly.

$G(\mathbf{x}'\boldsymbol{\beta})$ of the (conditional) probability of school attendance, $\pi_2(\mathbf{x}'\boldsymbol{\beta}) = G(\mathbf{x}'\boldsymbol{\beta}) = \frac{\exp(\mathbf{x}'\boldsymbol{\beta})}{1+\exp(\mathbf{x}'\boldsymbol{\beta})} = \Lambda(\mathbf{x}'\boldsymbol{\beta})$, which here is the logistic distribution. Assume that the conditional mean is correctly specified as $E(n_2^b|\mathbf{x}, N_2) = N_2\pi_2(\mathbf{x}'\boldsymbol{\beta})$ and the conditional probability of the number of children attending primary school being equal to n_2^b is $\Pr(y = n_2^b|\mathbf{x}) = \binom{n_2^b}{N_2}\pi_2(\mathbf{x}'\boldsymbol{\beta})^{n_2^b}(1-\pi_2(\mathbf{x}'\boldsymbol{\beta}))^{N_2-n_2^b}$. The log-likelihood function for each household is then given by

$$\ln L(\beta) = \ln \binom{n_2^b}{N_2} + n_2^b \ln \Lambda(\mathbf{x}'\boldsymbol{\beta}) + (N_2 - n_2^b)\ln(1 - \Lambda(\mathbf{x}'\boldsymbol{\beta}))$$

and the first order conditions with respect to $\boldsymbol{\beta}$ is given by

$$\frac{\partial \ln L}{\partial \boldsymbol{\beta}} = n_2^b\mathbf{x} - N_2\left(\frac{\exp(\mathbf{x}'\boldsymbol{\beta})}{1 + \exp(\mathbf{x}'\boldsymbol{\beta})}\right)\mathbf{x} = \left(n_2^b - E(n_2^b|\mathbf{x}, N_2)\right)\mathbf{x} = 0$$

the solution to which is the maximum likelihood estimator $\hat{\boldsymbol{\beta}}_{ML}$.

However, maximum likelihood estimation requires the underlying binomial distribution to be correctly specified, that is assuming homogeneity and independence concerning school attendance among the children of a household. If these assumptions do not hold, the model generates over- or under-dispersion relative to the specified distribution variance of n_2^b. By using the quasi-maximum likelihood estimator, that is finding the $\boldsymbol{\beta}$ that satisfies the first order condition rather than the $\boldsymbol{\beta}$ that maximises the likelihood function above, it is possible to relax the distributional assumptions concerning the conditional variance and instead allow for the robust sandwich estimator initially introduced by Huber (1967). The conditional variance of n_2^b, which is part of the robust sandwich estimator of $var(\boldsymbol{\beta})$, is then simply estimated by $\widehat{Var(n_2^b|\mathbf{x}, N_2)} = (n_2^b - \widehat{E(n_2^b|\mathbf{x}, N_2)})^2$, where $\widehat{E(n_2^b|\mathbf{x}, N_2)} = N_2\pi_2(\mathbf{x}'\hat{\boldsymbol{\beta}})$. The sandwich estimator is robust to over- and under-dispersion, heteroskedasticity, distributional misspecification and clustering, as long as the conditional mean is correctly specified, (Cameron and Trivedi (1998), Newson (1999) and Wooldridge (2002)). Thus, this variance estimator is robust to violation of the assumptions of homogeneity and independence among the school-aged children in the household.

4.2   Empirical Results

There are three testable empirical implications of the three period portfolio model. First of all, an implication of the need for future risk diversification is that, given enough uncertainty about future income transfers, there will be negative sibling dependence among the younger and older cohorts of siblings. Second, this should primarily hold for siblings in rural households, because urban households do not have the same diversification possibilities between formal and traditional education. Third, it should also only hold for sons and not for daughters due to the patrilineal structure of the Tanzanian society. The model is therefore in principle only

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applicable to rural sons.

(Table 2)

Column 1 in table 2 is a binomial regression of the number of primary school attending sons from cohort 2 out of the total number of sons in cohort 2, N_2. It is regressed on π_1, N_1 of older brothers and N_2 as well as on proxies for the remaining model variables. Household income is proxied by the expenditure measure and a control for whether agriculture is the main source of income as well as an interaction term taking the parental agricultural earning abilities into account. Costs of schooling e^b are proxied by the average school cost in the village as well as the average distance to the local primary school in the village. Finally, an indicator variable for whether the household has a herd or not is included, this is thought as a proxy for e^a. The key variable of interest is the effect of π_1 on π_2 (which in effect is the dependent variable) among rural sons.

When π_1 enter as a linear term in the π_2 regression, it has no significant effect on π_2. However, if the effect of π_1 is allowed to be non-linear and a quadratic term is included, it is soon clear that the insignificance of the linear term is due to the underlying non-linearity. There is both a strong positive effect of π_1 on π_2 for lower levels of π_1 and a strong negative effect for higher levels of π_1. The turning point is constant across the three specifictions for rural sons in column 2-4, which allow for different sets of control vairables. In column 2 only the model proxies are included, column 3 also includes school quality controls and column 4 in addtion includes a number of household characteristics as well as tribal controls and religious affiliation. Somewhat surprisingly, apart from the quadratic π_1 terms, only the latter group is (jointly) significant. A series of other control variables have all been tested insignificant and without any influence of the π_1 estimated coefficients.

The turning point of the inverse U equals 0.57 for all three specifications in column 2-4. Below this point, the positive relationship between π_1 and π_2 is either due to the ameliorating effect of N_2 children on the liquidity constraints or simply a consequence of cross-sectional heterogenity in π^*, as illustrated in figure 4 and 5. It is impossible to separate which of these two positive effects are dominating. However, this is not true when it comes to the negative effect of π_1 on π_2 for higher levels of π_1. The model predicts that when there is no uncertainty about future income transfers, there will always be a positive effect of π_1 on π_2 due to the positive income effect. Only a considerable degree of uncertainty and thus a strong enough need to diversify risk by diversifying income sources can generate a negative effect of high levels of π_1 on π_2. That such a negative effect exists for rural sons cannot be rejected. It even exists for a substantial part of the N_1 distribution, only 30.46% of the rural households with sons have $\pi_1 \leq 0.57$ among sons. Thus, for a majority of younger sons, the parental need for future risk diversification seems to be a main determinant for their schooling decision.

The picture is different for rural daughters. The schooling rate of younger daughters (π_2) is estimated in column 5. There is no significant effect of schooling of their older sisters, irrespective of the functional form. Column 4 reports the quadratic effect, but a pure linear effect is also insignificant, although in some specifications a positive effect of the linear term is significant at 10%. The π_1 terms for rural daughters cannot be tested jointly significantly different from zero, they can also not be tested jointly significantly different from the two π_1 coefficients of the rural sons. There is too much imprecision to say anything conclusive about whether there is positive or negative sibling dependence among sisters. The schooling decision of girls do, however, seem to respond to income effects. There is a positive significant (at 10%) effect of log of household expenditure on schooling of the younger cohort of sisters with a high marginal effect of 32% for the average rural household with daughters. The distance to the local primary school also matters significantly. Calculating the marginal effect, an extra kilometer in terms of distance can reduce the proportion of younger sisters in school by 8 percentage points. Overall, it seems safe to conclude that for daughters it is unlikely to be portfolio effects among sisters, which dominate the schooling decisions made by parents, but there could be some degree of sister rivalry. This gender difference between sons and daughters is consistent with the risk diversifcation hypothesis, but not with the possible alternative of $\pi^* < 1$ due to within household ability differences.

There is a lot of imprecision in the estimates for both sons and daughters when the sample is split by gender. This is not surprising. First of all, only households, which have children of the same gender in both the younger and older cohort, are included. Second, there is less variation in the dependent variable because there are fewer N_2 sons or N_2 daughters, this will generate more corner solutions. Furthermore, there might be size effects from splitting the sample. More corner solutions can in itself generate stronger negative effects of π_1. However, if results were purely driven by size effects, they should be stronger for daughters than for sons because the sample for daughters is smaller than that for sons. This is not the case.

Households are aggregated to include all siblings of rural households in column 6 and, for comparison, of urban households in column 7. Finally, the model is also estimated on the full sample in column 8, which naturally increases the level of precision in the coefficient estimates. Now household expenditure has a strong significantly positive effect, and there is a negative effect of high levels of agricultural income, consistent with traditional education being a relatively more attractive educational alternative. But what is more important, is that the non-linear quadratic effects of π_1 on π_2 are also strongly significant on the full sample. In fact, they seem stronger for the full sample than for the rural sample, indicating that the size effects are likely to be negligible. The turning point of the inverse U of π_2 is now higher and very close to the actual rate of schooling in the data, $\pi^* = 0.7$. When looking at colum 6 and 7, however, it is clear that the quadratic effect stems from the rural households. Among urban

households there is a positive linear effect of π_1 on π_2, but the quadratic terms is insignificant. A joint test for whether the two π_1 terms for urban households in column 7 equals those of the rural households in column 6 is rejected at a 5% level, indicating that there is very limited scope for human capital diversification among siblings in urban households. Thus, the model implications of risk and income source diversification generating negative sibling dependence among older and younger siblings in rural households and, within these, primarily among sons, cannot be rejected by the data.

(Table 3)

The results are robust over a range of empirical specifications with the inclusion or exclusion of a number of different control variables, such as whether households have electricity, bank accounts, access to transport, and ownership of own house. From table 3 it also shows that, in addition, results are robust to choice of econometric model. The qualitative findings are the same both for the full sample of households, as well as when the sample is split by rural or urban households. The turning point for the inverse U of π_1 is also reasonable stable over the different specifications. It is 0.75 and 0.77 for the full sample in the Tobit model and the linear probability model, respectively, and 0.63 and 0.65 for the rural households in the same two models. This has to be compared with 0.7 and 0.63 for the full sample and the rural households, respectively, in the binomial model.

5   Conclusion and Policy Implications

The main contribution of this paper is to extend a simple two-period human capital portfolio model, which allows for two types of education with different returns and different risk, such that it can generate empirical predictions directly testable in standard household data from developing countries. By extending the model to a three-period model and allowing for sequentiality in the human capital investment decision of siblings, it is possible to derive testable model predictions of sibling dependence due to risk diversification, which differ from predictions based on sibling rivalry over scarce resources.

The key implication of the two-period model is that uncertainty about future income transfers from children generates a need for future risk and thus income source diversification, which spills over into a need for current human capital diversification in the educational choice of children. This human capital diversification is only possible in rural areas, where there exists a clear dichotomy between formal and traditional education and the associated future urban and agricultural employment. Traditional education in terms of on-farm learning by doing endows children with specific skills or human capital directing them towards future agricultural work or farming. Formal education, on the other hand, endows children with general human capital

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suitable for future modern or urban employment. As long as returns and risks of the agricultural and the urban sector are uncorrelated, an obvious ex-ante risk management strategy of income smoothing is simply to ensure an optimal balancing of risk and returns from these two sectors by diversifying the human capital portfolio of children already when they are of school age.

Model implications makes it possible to disentangle sibling dependency due to risk diversification from the standard argument of sibling rivalry over scarce resources in the child labour literature. The testable empirical prediction is that there should be a negative relationship between schooling of the younger and older sibling cohorts. The empirical analysis shows that such a negative sibling dependence does indeed exist when the proportion of formally educated older siblings is high, consistent with a need ofr risk diversification due to uncertainty about future returns to education. The result holds for the full sample of households, and when looking into the specific subsamples, it holds for rural households and not for urban, and it is only strong and significant for the specific subsample of rural sons, exactly as expected considering the human capital portfolio model.

The question is then whether such a negative effect for the specific subsample of rural sons could be caused by something else. First, it cannot be explained by liquidity constraints, because these older siblings beyond school age typically contribute to household income. Second, birth order effets, which are often used as a prime indicator for whether or not a child is attending school in empirical analyses based on individual children, would also predict the opposite effect. It is generally thought that the older siblings work to help pay for schooling of the younger ones, the effect should therefore be positive. Third, the negative effect of a high proportion of schooling of older siblings on the proportion of schooling of the younger ones is also not likely to be caused by transitory income shocks. Transitory income shocks in rural areas are generally caused by failing agricultural income (e.g. due to adverse weather conditions), households with older formally educated siblings and thus access to urban income sources should be able to shield the schooling of the younger siblings better than households without, which would generate a positive rather than a negative relationship. Finally, within household ability differences could be generating the same overall results. Within household ability differences would also result in an over $\pi^* < 1$ with a mechanical negative relationship between π_1 and π_2 as found in the simulations. However, within household ability differences cannot explain the empirical findings in terms of gender differences and rural-urban differences.

The final conclusion is therefore that future income uncertainty and the need for risk diversification does affect the joint schooling decision to such an extent that there is negative sibling dependence between cohorts. The return side of the human capital investment decision can thus be a dominating factor in the human capital investment decision made by parents on behalf of their children. I do not wish to question the importance of liquidity constraints on the

schooling decision of children, in fact I also find some evidence of income effects, however what I do question is whether the liquidity constraint explanation, which only relates to the cost side of the human capital investment decision is indeed the full explanation. Taking the return side into consideration when analysing the human capital investment decisions of parents has important implications for educational policies. If the objective of policy makers is to ensure full enrolment into primary schools, lowering the costs of schooling will have a positive, but insufficient effect for the objective to be reached in rural areas where traditional agricultural production systems require specific skills, passed on by generations. Only in modern more complex agricultural production systems, where there are 'learning opportunities' from general human capital skills, as Rosenzweig (1995) puts it, will formal schooling generate a return. When the production technology is simple, there are generally very limited or no returns to formal schooling, e.g. Foster and Rosenzweig (1996), Fafchamps and Quisumbing (1999) and Jolliffe (2004). Parents, I am sure, perceive this.

So, is it possible to generate returns to formal schooling in simple agriculture? What if primary schooling did not only endow children with general human capital in terms of mathematics and reading and writing Kiswahili and English (as it is the case in Tanzania, where a third, tribal, language is the mother tongue of most children), but also endowed children in rural areas with some of the specific skills needed for a future life in farming? That is, adapting the curricula of primary education to the future needs and necessary life skills of the children supposed to attend school. As a matter of fact, the parents of the HRDS data give the answer themselves. In the survey, they have been asked a number of questions about education and school curricula, including a question on what they think are the important subjects that *should be* taught in primary schools[14]. They were asked to rank five subjects according to importance: (i) 'teaching good written and spoken Kiswahili', (ii) 'teaching good written and spoken English', (iii) 'religious or moral education that teaches children to be polite, respectful and good citizens', (iv) 'teaching technical skills for agriluture and business' (which is the only course out of the five that is not actually being taught), and (v) 'teaching mathematics and science'. There is no doubt about their answer, teaching technical skills for agriculture and business rank highest. Parents want, not only general, but also specific skills for their children. They want skills diversification.

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[14]Section 2, part B, question 80-85 in the HRDS questionnaire.

References

BEEGLE, K., R. DEHEJIA, AND R. GATTI (2006): "Child Labor and Agricultural Shocks," *Journal of Development Economics*, 81(1), 80–96.

BEKOMBO, M. (1981): "The Child in Africa: Socialisation, Education and Work," in *Child Work, Poverty and Underdevelopment*, ed. by G. Rodgers, and G. Standing, chap. 4, pp. 113–130. International Labour Office.

BOCK, J. (2002): "Learning, Life History, and Productivity. Children's Lives in the Okavango Delta, Botswana," *Human Nature*, 13(2), 161–197.

CAMERON, A., AND P. TRIVEDI (1998): *Regression Analysis of Count Data*. Cambridge University Press, UK.

DEATON, A. (1998): *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*. Johns Hopkins Univ Pr.

EDMONDS, E. V. (2007): "Child Labor," in *Handbook of Development Economics*, ed. by T. Schultz, and J. Strauss, vol. 4. Elsevier Science, Amsterdam, North-Holland.

ESTEVAN, F., AND J. BALAND (2007): "Mortality Risks, Education and Child Labor Star, Open," *Journal of Development Economics*, 84(1), 118–137.

FAFCHAMPS, M., AND A. QUISUMBING (1999): "Human Capital, Productivity, and Labor Allocation in Rural Pakistan," *The Journal of Human Resources*, 34(2), 369–406.

FOSTER, A., AND M. ROSENZWEIG (1996): "Technical Change and Human-Capital Returns and Investments: Evidence from the Green Revolution," *The American Economic Review*, 86(4), 931–953.

GROOTAERT, C., AND R. KANBUR (1995): "Child Labor: An Economic Perspective," *International Labor Review*, 134(2), 187–203.

HUBER, P. (1967): "The Behavior of Maximum Likelihood Estimates under Nonstandard Conditions," *Proceedings of the Fifth Berkeley Symposium in Mathematical Statistics*, 1, 221–233.

JACOBY, H., AND E. SKOUFIAS (1997): "Risk, Financial Markets and Human Capital in a Developing Country," *Review of Economic Studies*, 64, 311–336.

JENSEN, R. (2000): "Agricultural Volatility and Investments in Children," *The American Economic Review*, 90(2), 399–404.

JOLLIFFE, D. (2004): "The Impact of Education in Rural Ghana: Examining Household Labour Allocation and Returns on and of the Farm," *Journal of Development Economics*, 73, 287–314.

LASSEN, D. D., AND H. B. LILLEØR (2008): "Informal Institutions and Intergenerational Contracts: Evidence from Schooling and Remittances in Rural Tanzania," mimeo. University of Copenhagen.

LILLEØR, H. B. (2008): "Can Future Uncertainty Keep Children Out of School?," Centre for Applied Microeconometrics, University of Copenhagen.

MORDUCH, J. (1995): "Income Smoothing and Consumption Smoothing," *The Journal of Economic Perspectives*, 9(3), 103–114.

——— (2000): "Sibling Rivalry in Africa," *American Economic Review, Papers and Proceedings*, 90(2), 405–409.

NEWSON, R. (1999): "Robust Variance Estaimates for Generalised Linear Models," *Stata Technical Bulletin*, 50, 27–34.

POULIOT, W. (2005): "Introducing Uncertainty Into Baland and Robinson's Model of Child Labour," *Journal of Development Economics*.

RODGERS, G., AND G. STANDING (1981): *Child Work, Poverty and Underdevelopment*. International Labour Office.

ROSENZWEIG, M. (1995): "Why Are There Returns to Schooling?," *The American Economic Review*, 85(2), 153–158.

THOMAS, STRAUSS, AND HENRIQUES (1990): "Child Survival, Height for Age and Household Characteristics in Brazil," *Journal of Development Economics*, 33, 197–234.

WINKELMAN, R. (1997): *Econometric Analysis of Count Data*. Springer-Verlag, Berlin, 2nd edn.

WOOLDRIDGE, J. (2002): *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

6 Figures

Figure 1. Effect of uncertainty ε on optimal overall proportion of siblings in school π^*
   - under no liquidity constraints and no child labour ($e^a = 0.0125$)
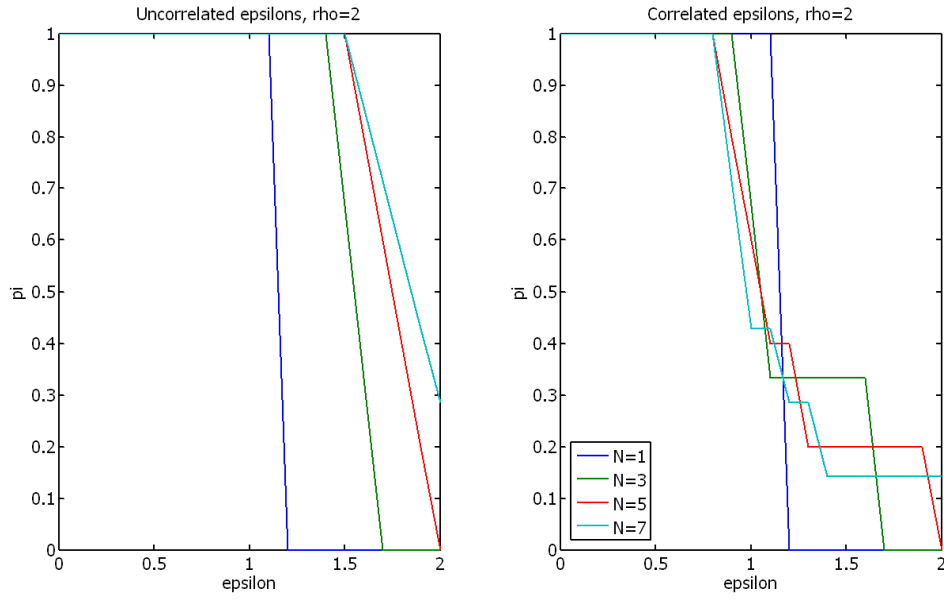
Figure 2. Effect of uncertainty ε on optimal overall proportion of siblings in school π^*
- under liquidity constraints and child labour ($e^a = -0.025$)
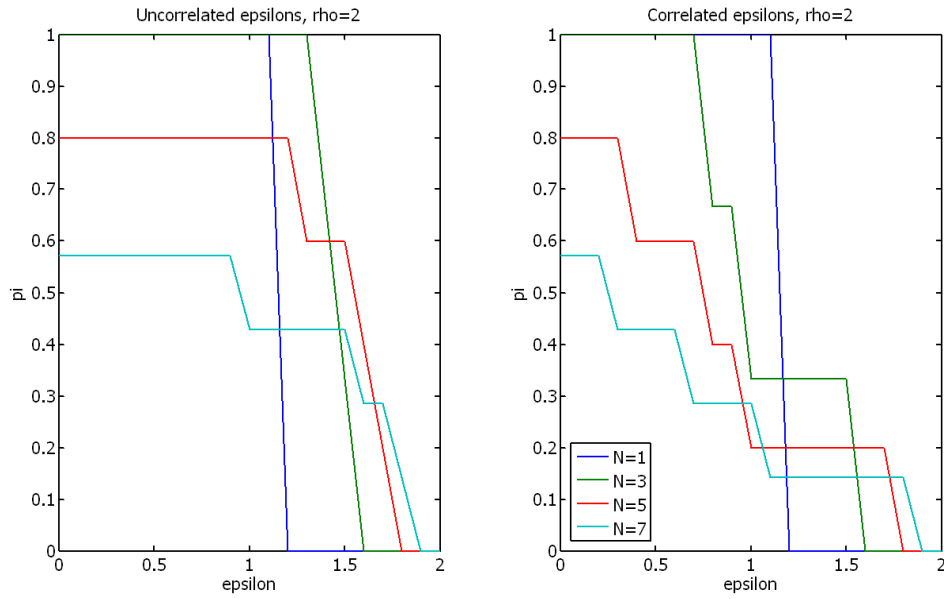
Figure 3. Effect of older cohort's π_1 on younger cohort's π_2

- under no liquidity constraints and no child labour $(s \lesseqgtr 0, e^a = 0.0125)$

- under no correlation over time and perfect correlation within cohorts and between cohorts
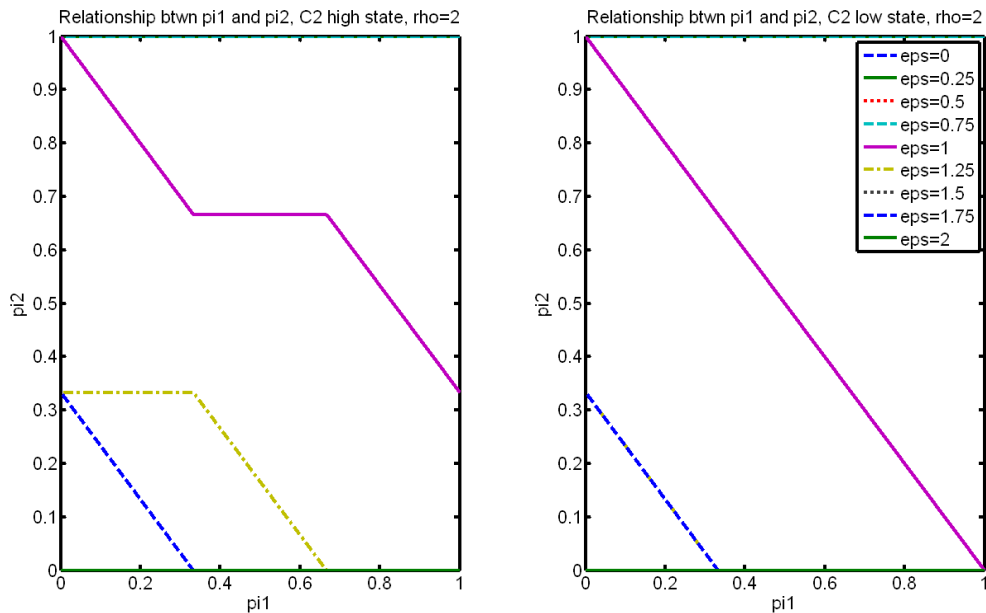
Figure 4. Estimation of π_1 and π_2 relationship on simulated data for full distribution of π^*

Figure 5. Estimation of π_1 and π_2 relationship on actual data for full distribution of π^*

Figure 6. Effect of older cohort's π_1 on younger cohort's π_2
- under liquidity constraints and child labour $(s \geq 0, e^a = -0.025)$
- under no correlation over time and perfect correlation within and between cohorts

7 Tables

Table 1. Summary statistics

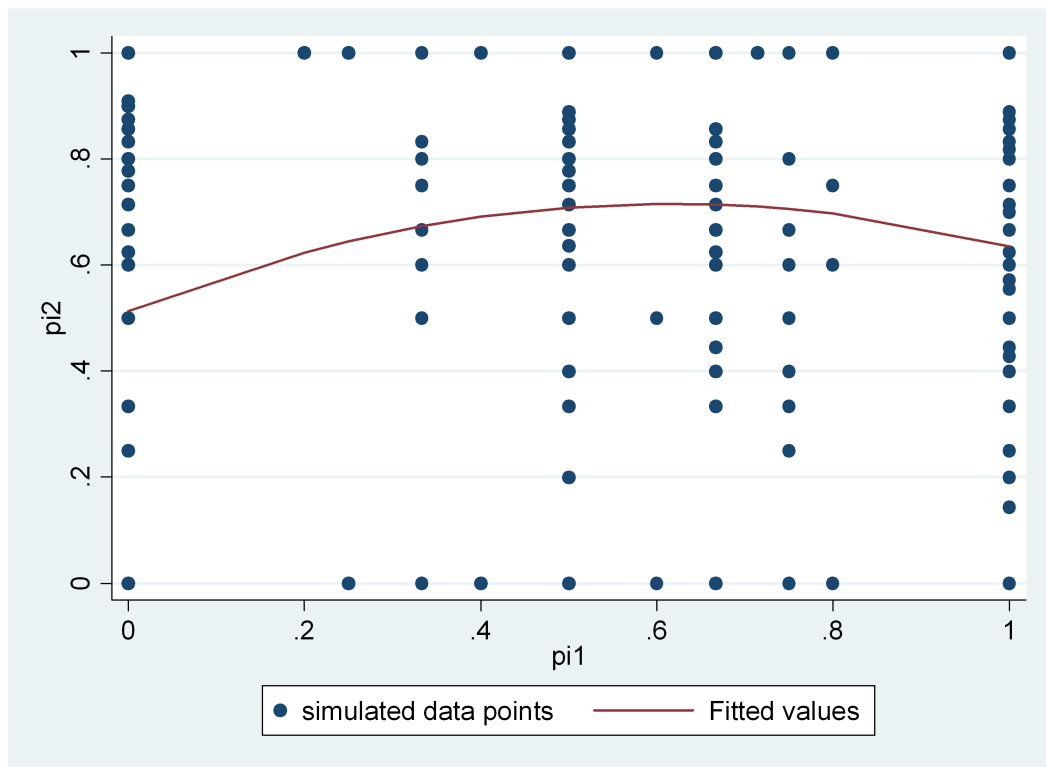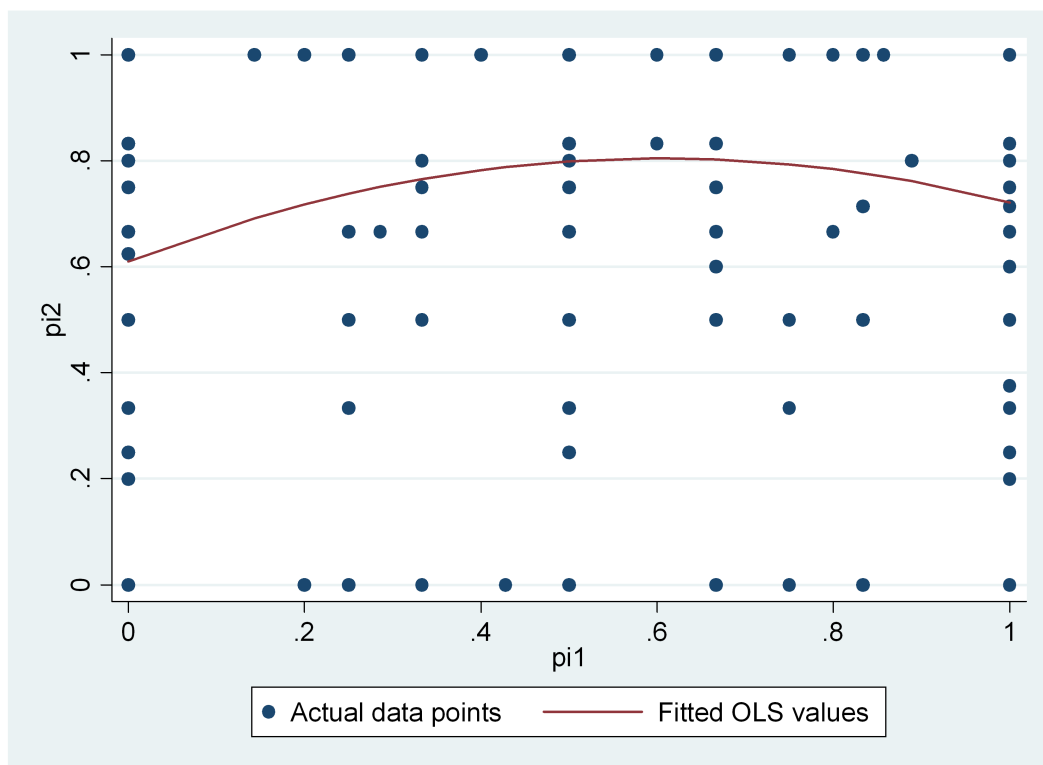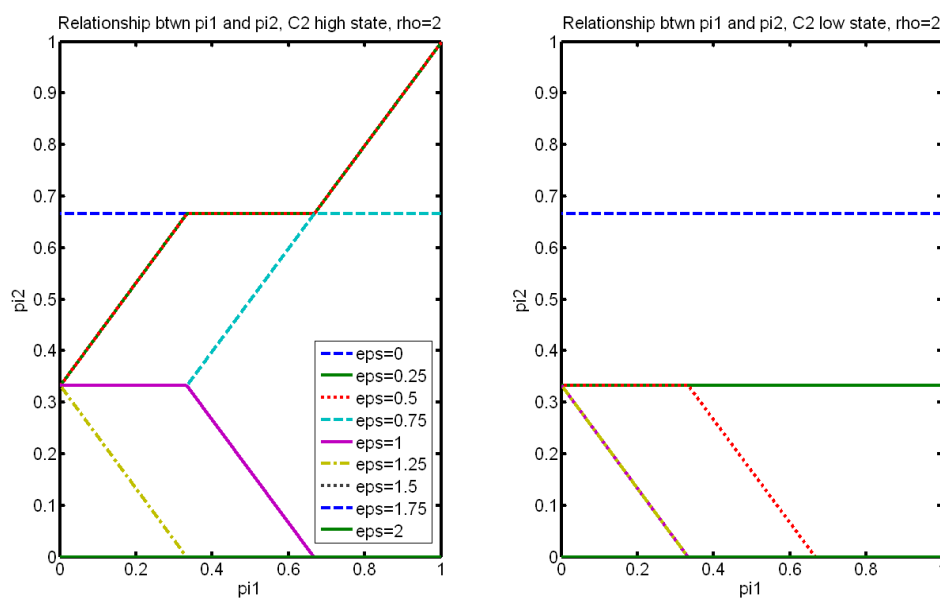|	Rural HHs				Urban HHs			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Sibling composition								
pi	0.715	0.260	0.000	1.000	0.787	0.274	0.000	1.000
pi1	0.721	0.329	0.000	1.000	0.780	0.347	0.000	1.000
pi1 (sons)	0.710	0.393	0.000	1.000	0.755	0.397	0.000	1.000
pi1 (daughters)	0.721	0.393	0.000	1.000	0.812	0.358	0.000	1.000
pi2	0.741	0.386	0.000	1.000	0.799	0.354	0.000	1.000
pi2 (sons)	0.739	0.398	0.000	1.000	0.808	0.368	0.000	1.000
pi2 (daughters)	0.746	0.411	0.000	1.000	0.808	0.370	0.000	1.000
N2 children in school	1.633	1.067	0.000	6.000	1.635	1.067	0.000	6.000
N2 sons in school	0.833	0.801	0.000	4.000	0.820	0.822	0.000	4.000
N2 daughters in school	0.800	0.856	0.000	4.000	0.815	0.821	0.000	4.000
N1	2.306	1.248	1.000	10.000	2.108	1.059	1.000	6.000
N1 sons	1.187	0.942	0.000	5.000	1.092	0.881	0.000	4.000
N1 daughters	1.119	1.000	0.000	6.000	1.016	0.893	0.000	4.000
N2	2.063	1.297	1.000	9.000	2.288	1.386	1.000	9.000
N2 sons	1.179	1.060	0.000	8.000	1.181	1.029	0.000	6.000
N2 daughters	0.884	0.919	0.000	5.000	1.107	1.033	0.000	6.000
Proportion of daughters	0.461	0.236	0.000	1.000	0.484	0.232	0.000	1.000
N	5.606	2.342	2.000	19.000	5.289	1.921	2.000	15.000
Household characteristics								
HH expenditure per AE per day	0.708	0.501	0.125	5.213	1.260	1.218	0.130	14.008
Agriculture is main income	0.904	0.295	0.000	1.000	0.344	0.475	0.000	1.000
Av. school costs in village	6.369	3.567	1.718	19.281	19.129	13.190	1.622	82.135
Av school distance (km)	1.542	1.033	0.185	5.417	1.317	0.627	0.111	3.625
HH has livestock	0.413	0.493	0.000	1.000	0.082	0.274	0.000	1.000
Land(ha)	14.682	14.696	0.000	125.000	6.058	14.759	0.000	250.000
HH size	8.508	3.219	3.000	32.000	8.093	2.780	3.000	25.000
HH head female	0.099	0.299	0.000	1.000	0.145	0.353	0.000	1.000
Muslim HH	0.277	0.448	0.000	1.000	0.567	0.496	0.000	1.000
Catholic HH	0.346	0.476	0.000	1.000	0.218	0.413	0.000	1.000
Protestant HH	0.265	0.441	0.000	1.000	0.148	0.356	0.000	1.000
Village prop. of HHs w wage income	0.164	0.118	0.000	0.565	0.571	0.218	0.053	1.222
Village prop. of HHs w business income	0.046	0.056	0.000	0.273	0.122	0.081	0.000	0.500
School quality assesment								
Teachers good/adequate	0.746	0.436	0.000	1.000	0.881	0.324	0.000	1.000
Headmaster good/adequate	0.823	0.382	0.000	1.000	0.917	0.276	0.000	1.000
School supplies good/adequate	0.411	0.492	0.000	1.000	0.454	0.498	0.000	1.000
Environment good/adequate	0.552	0.498	0.000	1.000	0.656	0.475	0.000	1.000
Self-reliance good/adequate	0.798	0.402	0.000	1.000	0.828	0.378	0.000	1.000
Swahili lessons good/adequate	0.869	0.338	0.000	1.000	0.932	0.252	0.000	1.000
English lessons good/adequate	0.593	0.492	0.000	1.000	0.731	0.444	0.000	1.000
Math lessons good/adequate	0.777	0.417	0.000	1.000	0.855	0.353	0.000	1.000
Moral lessons good/adequate	0.728	0.445	0.000	1.000	0.818	0.387	0.000	1.000
Max number of observations	**654**				**674**			

Table 2. Robust binomial regressions of n_2^b given N_2

	1	2	3	4	5	6	7	8
Dependent variable: nb2 out of N2	Rural Sons	Rural Sons	Rural Sons	Rural Sons	Rural Daughters	Rural HHs	Urban HHs	All HHs
pi1	0.251	3.706***	3.630***	3.760***	3.284	1.867**	2.211**	2.134***
	(0.248)	(1.378)	(1.373)	(1.405)	(2.622)	(0.816)	(1.017)	(0.613)
pi1 squared		-3.282**	-3.185**	-3.330**	-2.729	-1.476*	-1.314	-1.514***
		(1.275)	(1.275)	(1.300)	(2.580)	(0.772)	(0.916)	(0.566)
N2	-0.100	-0.128	-0.118	-0.189	-0.133	-0.034	-0.041	-0.032
	(0.097)	(0.092)	(0.090)	(0.126)	(0.162)	(0.062)	(0.085)	(0.050)
N1	0.112	0.021	0.054	0.028	0.393	0.195***	-0.064	0.080*
	(0.109)	(0.096)	(0.093)	(0.119)	(0.283)	(0.065)	(0.069)	(0.047)
Proportion of daughters	0.408	0.426	0.480	0.287	0.140	0.066	0.154	0.077
	(0.497)	(0.467)	(0.462)	(0.645)	(0.799)	(0.268)	(0.316)	(0.202)
ln(HH expenditure per AE per day, USD)	-0.694	-0.649	-0.607	-0.671	1.038*	0.423**	0.498***	0.475***
	(0.809)	(0.752)	(0.713)	(0.712)	(0.572)	(0.199)	(0.193)	(0.152)
ln(HH exp)*Agri. main income	0.896	0.863	0.867	0.863	-0.688	-0.231	-0.429*	-0.305*
	(0.835)	(0.778)	(0.742)	(0.725)	(0.607)	(0.227)	(0.248)	(0.174)
Agriculture is main income	0.286	0.366	0.435	0.514	-0.717	-0.236	0.003	-0.021
	(0.577)	(0.556)	(0.530)	(0.536)	(0.589)	(0.215)	(0.173)	(0.128)
Av. annual school costs in village, USD	0.025	0.021	0.009	-0.012	0.031	0.017	0.006	0.003
	(0.028)	(0.028)	(0.031)	(0.037)	(0.046)	(0.026)	(0.010)	(0.007)
Av school distance (km)	-0.082	-0.066	-0.077	-0.087	-0.264**	-0.083	-0.379***	-0.141***
	(0.081)	(0.087)	(0.093)	(0.095)	(0.127)	(0.059)	(0.121)	(0.054)
HH has livestock	-0.241	-0.301	-0.302	-0.311	0.097	-0.214	-0.235	-0.158
	(0.187)	(0.183)	(0.198)	(0.211)	(0.288)	(0.135)	(0.305)	(0.126)
Land (ha)				-0.002	0.013	0.002	0.017	0.005
				(0.006)	(0.009)	(0.004)	(0.011)	(0.004)
HH size				0.020	-0.029	-0.028	0.023	-0.013
				(0.037)	(0.048)	(0.024)	(0.047)	(0.021)
HH head female				-0.356	0.261	-0.222	0.318	0.048
				(0.400)	(0.438)	(0.187)	(0.297)	(0.167)
Village prop. of HHs w wage income				0.440	-1.184	-0.077	1.665***	0.535**
				(0.854)	(1.092)	(0.516)	(0.456)	(0.267)
Village prop. of HHs w business income				-0.189	10.228***	3.158**	2.786**	2.322***
				(2.194)	(2.254)	(1.406)	(1.263)	(0.805)
Constant	0.534	0.462	0.304	0.553	0.596	0.638	-1.003	0.145
	(0.656)	(0.619)	(0.692)	(0.754)	(1.029)	(0.440)	(0.661)	(0.337)
School quality controls	No	No	Yes	Yes	Yes	Yes**	Yes	Yes***
Tribal and religious controls	No	No	No	Yes***	Yes***	Yes***	Yes***	Yes***
Observations	363	363	363	363	281	654	674	1328

Robust cluster corrected standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 3. Robustness check of econometric model

	Tobit model			Linear probability model		
Dependent variable: pi2	**All HHs**	**Rural HHs**	**Urban HHs**	**All HHs**	**Rural HHs**	**Urban HHs**
pi1	1.178***	1.092***	1.024	0.402***	0.406***	0.320
	(0.396)	(0.392)	(0.805)	(0.133)	(0.154)	(0.214)
pi1 squared	-0.788**	-0.873**	-0.314	-0.261**	-0.314**	-0.114
	(0.359)	(0.364)	(0.705)	(0.117)	(0.139)	(0.182)
N2	-0.119***	-0.083***	-0.196***	-0.011	-0.012	-0.011
	(0.029)	(0.032)	(0.058)	(0.010)	(0.014)	(0.014)
N1	0.052*	0.121***	-0.062	0.017**	0.045***	-0.010
	(0.028)	(0.035)	(0.050)	(0.009)	(0.012)	(0.011)
Proportion of daughters	-0.071	-0.079	0.003	-0.018	-0.029	0.009
	(0.126)	(0.137)	(0.247)	(0.041)	(0.057)	(0.058)
ln(HH expenditure per AE per day, USD)	0.271***	0.350***	0.238*	0.079***	0.130***	0.058**
	(0.088)	(0.121)	(0.131)	(0.025)	(0.045)	(0.029)
ln(HH exp)*Agri. main income	-0.145	-0.237*	-0.129	-0.036	-0.080	-0.034
	(0.099)	(0.134)	(0.186)	(0.029)	(0.049)	(0.042)
Agriculture is main income	-0.015	-0.149	0.001	-0.001	-0.050	0.003
	(0.082)	(0.144)	(0.133)	(0.024)	(0.054)	(0.030)
Av. annual school costs in village, USD	0.001	0.007	0.006	-0.000	0.004	0.000
	(0.004)	(0.012)	(0.006)	(0.001)	(0.005)	(0.001)
Av school distance (km)	-0.121***	-0.073**	-0.329***	-0.039***	-0.032**	-0.083***
	(0.030)	(0.031)	(0.088)	(0.011)	(0.015)	(0.023)
HH has livestock	-0.112	-0.125*	-0.194	-0.047*	-0.062**	-0.040
	(0.073)	(0.067)	(0.202)	(0.026)	(0.030)	(0.047)
Land (ha)	0.003	0.001	0.010*	0.000	0.000	0.001
	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)
HH size	-0.000	-0.016	0.037	-0.000	-0.006	0.007
	(0.013)	(0.013)	(0.032)	(0.004)	(0.006)	(0.007)
HH head female	0.006	-0.104	0.133	-0.005	-0.042	0.024
	(0.098)	(0.104)	(0.202)	(0.030)	(0.042)	(0.046)
Village prop. of HHs w wage income	0.201	-0.026	0.879***	0.050	0.004	0.189***
	(0.158)	(0.270)	(0.308)	(0.048)	(0.114)	(0.072)
Village prop. of HHs w business income	1.211***	1.761***	1.721**	0.330**	0.629***	0.399*
	(0.456)	(0.598)	(0.859)	(0.135)	(0.238)	(0.206)
Constant	0.882***	1.060***	0.171	0.602***	0.692***	0.393***
	(0.201)	(0.254)	(0.460)	(0.069)	(0.102)	(0.126)
Observations	1328	654	674	1328	654	674
R-squared	.	.	.	0.117	0.128	0.159

Robust cluster corrected standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

8 Appendix A1

Under no liquidity constraints and no child labour, the derivative of π_2 with respect to π_1 is found by using Cramer's rule on the system of first order conditions. It is given by

$$\frac{d\pi_2}{d\pi_1} = \frac{ED - BF}{AD - BC}$$

where

$$
\begin{aligned}
A &= D = \left[-(e^b - e^a) N_2 U''(c_2) - E\left(N_2 N^{-\alpha_3} (y_{23}^b - y_3^a) U''(c_3) \right) \right] > 0 \\
B &= \left[-U''(c_2) - EU''(c_3) \right] > 0 \\
C &= \left[-\left((e^b - e^a) N_2 \right)^2 U''(c_2) - E\left(\left(N_2 N^{-\alpha_3} (y_{23}^b - y_3^a) \right)^2 U''(c_3) \right) \right] > 0 \\
E &= \left[E\left(N_1 N^{-\alpha_3} (y_{13}^b - y_3^a) U''(c_3) \right) - N_1^{1-\alpha_2} (y_{12}^b - y_2^a) U''(c_2) \right] < 0 \\
F &= \left[E\left(N^{-2\alpha_3} N_2 (y_{23}^b - y_3^a) N_1 (y_{13}^b - y_3^a) U''(c_3) \right) - (e^b - e^a) N_1^{1-\alpha_2} N_2 (y_{12}^b - y_2^a) U''(c_2) \right] < 0
\end{aligned}
$$

Although not immediate from above, it turns out that the derivative is generally negative and in particularly so the larger the uncertainty.

Under liquidity constraints ($s = 0$) and child labour ($e^a < 0$), the derivative is simply given by

$$\frac{d\pi_2}{d\pi_1} = \frac{F}{C}$$

which is by all means easier to interpret. The sign depends on F, which now is ambiguous because consumption smoothing over time is difficult. If there is virtually no uncertainty (as it is typically the case in the standard child labour literature), there are high indirect costs of schooling such that $(e^b - e^a)$ is large, and the household is severely liquidity constrained such that $|U''(c_2)| \gg |U''(c_3)|$ because second period consumption is smaller than third period consumption, then the second term in F will dominate and the derivative becomes positive. This positive effect is strengthened the larger the immediate gains from child labour in period 2 that is the higher the indirect costs of schooling $(e^b - e^a)$.