THE EFFECTS OF RISK ON EDUCATION IN INDONESIA

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Abstract

We study the effects of risk and uncertainty on education in Indonesia. Households that face more uncertainty, and that have limited or no access to formal insurance, will have a higher motive for self-insurance and this may have adverse consequences for investment in child education. A key contribution of the paper is to decompose risk into village- and household-level components, and to estimate whether they have different effects on education. We find no evidence of household risk affecting child education, however there is evidence that village risk adversely affects investment in education.

1. Introduction

The widely documented differences in children's school and work activities between high and low income countries are largely due to the different economic settings that underlie choices in both types of environment. The substantial differences in income levels between such economies is a key factor. Apart from lower income levels however, less developed countries (LDCs) are characterised by higher risk and lower opportunities for diversifying such risk, due to thin insurance markets and the relatively more acute presence of borrowing constraints. These particular features of low-income settings create the need for households to form alternative ways of coping with risk. This is borne out in the extensive literature that examines the importance of risk as a factor underlying the economic choices of households (Rosenzweig, 1988; Rosenzweig and Stark, 1989; Paxson, 1992; Rosenzweig and Binswanger, 1993; Kochar, 1995).

In this paper, we assess whether investment in education is affected by virtue of living in an environment that is inherently risky. To our knowledge, this is the first paper to consider how education choices respond to perceived future risk, as distinct from how they respond to the actual occurrence of adverse events. Moreover, we decompose ex-ante risk into components that are specific to the household, and those that are pervasive within the village in order to investigate whether they have differential effects on the stock of human capital of children. The distinction between the two types of risk is important, given the extensive evidence on the differing responses of economic agents to both.[1]

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[1] Townsend (1994) presents evidence that individuals are successful at insuring against idiosyncratic but not village-level shocks. Udry (1994) finds that individuals use credit markets to pool risks and deal with shocks ex-post within communities; the paper does not explicitly address community-wide shocks however. Rosenzweig and Binswanger (1993)

The underlying channel through which one might expect risk to affect education is as follows. The riskier the environment, the greater is the incentive of the household to build up a buffer stock against unforeseen adverse events. Children are one means of allowing the household to do this.[2] This is due to their instantaneous earnings potential as well as the option of curtailing expenditure on their education. The motive to amass a buffer stock will be higher, the less well-functioning are insurance markets.[3] In this sense, any finding that risk affects education, would be indicative of incomplete insurance markets. Moreover, the availability of insurance against risk is likely to depend on the pervasiveness of risk. Therefore by considering separately the effects of household risk and village risk on education, we can shed some light on the presence of insurance for dealing with different types of risk to which households are exposed.

In considering the extent to which living in an inherently risky environment affects investment in education, our contribution is distinct from those that examine the role of children as ex-post means of smoothing out income shocks. For example Jacoby and Skoufias (1997), Pörtner (2001), Ranjan (2001), Sawada and Lokshin (2001) and Beegle, Dehejia, and Gatti (2005) find that unanticipated shocks have positive effects on child labour, and Thomas et al (2004) find evidence that the Indonesian crisis adversely affected the education of young children in poor households. This strand of literature considers the

find that common weather shocks to income have greater effects on consumption than do idiosyncratic shocks to income.

[2]The role of a child as an insurance tool against unforeseen circumstances was proposed by Cain (1982).

[3]As Morduch (1995) discusses, the general consensus regarding insurance markets in LDCs is that even if, as is likely, household income is partly insurable, full insurance is highly unlikely; see also Townsend, 1995.

effects of adverse shocks on education ex-post, and is thus informative as to the presence of liquidity constraints. In contrast, we consider how education decisions are affected by *ex-ante* rather than ex-post forms of risk, given the insurance mechanisms in place. Our paper is therefore informative as to the presence of insurance against intrinsic income-related risk.

We develop a methodological framework for decomposing underlying risk into village- and household-level components, and consider the effects of each on child education. Essentially, we are equating risk with income variability: the idea is that even if two households have the same average income levels at a particular point, the underlying variance of the two income streams may differ, and this variability may affect schooling. We measure both the variability in the household-specific component of earnings, as well as the variability in the village-level component, using information on a time series of earnings of the household head. We go on to instrument both of these measures of variability, both for reasons of endogeneity and to deal with measurement error. We use past rainfall fluctuations to instrument village risk. For household risk, we use as instruments the interactions of past rainfall variability with the main occupation of the household head.

We find evidence in Indonesia that children living in rural households facing higher village-level risk have lower educational attainment than their counterparts in low-risk environments. We detect no discernible effects of household risk on children's education. These findings, observed in rural areas, are indicative of pervasive village risk being more difficult to insure against than idiosyncratic household risk, and provide some insight into the functioning of insurance markets in these villages. In particular, whilst household-level risk is being diversified away, whether through formal or informal mechanisms, without resorting to children, evidence that village risk affects education, suggests that insurance against this form of risk is not complete.

The remainder of the paper is structured as follows. In section 2 we outline a simple two-period model of investment in human capital in the context of a risky environment. We show conditions under which investment in human capital is negatively related to the earnings risk facing the financier of the child's schooling (the parent), though we go on to show how relaxing a key assumption renders the theoretical effects ambiguous. In section 3 we discuss both how we measure household risk and village risk and how we identify both of their effects on investment in education. In section 4 the Indonesian data used in the empirical analysis is described. Section 5 presents and discusses our main findings and section 6 concludes.

2.   Theory

In order to consider the theoretical implications of 'risk' on human capital investment, we set up a simple two-period framework in which education is an investment good, financed by parental income in the first period, but with the pecuniary payoffs accruing to the child in the second period, upon reaching adulthood. We first lay out a set of conditions under which the volatility of parental income - 'risk' - adversely affects investment in education. When we relax one of these conditions, we show that the effects become ambiguous.

The framework is such that in the first period, a household consists of one parent and one child.[4] The parent works and earns an exogenous income, y_1^p. A child's one unit of time is allocated between work and school. This decision is made by the parent, jointly with the consumption choice. The parent, whether due to imperfect capital markets and/or debt

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[4]We abstract from intra-household bargaining between parents over the child's activity (Basu, 2006), and compensating and reinforcing human capital decisions between siblings (Becker, 1991).

aversion, does not borrow to invest in schooling. The amount of time spent in school in this period, D_1, increases the child's stock of human capital, $H_1 = g(D_1)$, at a decreasing rate. In the second period the adult (this term is used to denote the grown-up child in the second period) earns y_2^a. This is increasing in the stock of human capital, and therefore in the amount of time spent in school as a child. For ease of notation, we write this in reduced form as $y_2^a = f(D_1)$.[5] The parent earns an exogenous income, y_2^p. We assume to begin with that there are no transfers from the adult to the parent in this period, so the motive for investment in education is purely altruistic on the part of the parent. We relax this assumption further below.

The parent chooses household consumption and child education at the beginning of period 1, without knowing its income for period 2, y_2^p. Assuming that preferences are intertemporally additive, the parent's problem is to

$$\max_{c_1^{hh}, D_1} U(c_1^{hh}) + \beta E_1 U(c_2^p) + \beta \gamma U(c_2^a) \tag{1}$$

subject to the life-cycle budget constraint

$$Y_L = c_1^{hh} + c_2^p + (p^D + w_1^c)D_1 \tag{2}$$

where c_i denotes consumption in that period, $i = 1, 2$, the superscripts hh, p and a refer to the household, parent and adult respectively, $c_2^a = y_2^a$, D_1 is the fraction of child time spent in school in period 1, β is the parental discount rate, γ measures the weight the parent places on the adult's utility, with $0 < \gamma < 1$, the expectations operator E_1 reflects uncertainty as at time 1 about y_2^p, and the individual period subutility functions are increasing and concave in their arguments. Y_L is the present value of the lifetime income of

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[5]We do not allow for a stochastic component to adult income in the second period, as the focus of this paper is on the riskiness of the *parental* income stream.

the parent, assuming that the labour market earnings of the child in period 1 are pooled with parental resources. Therefore $Y_L = y_1^p + y_2^p + w_1^c$, where w_1^c is full child income in period 1, which is not a function of human capital (Rosenzweig, 1980, and Jacoby and Skoufias, 1997), and p^D is the direct cost of schooling.

The first order condition for investment in education equates the utility-weighted expected marginal cost of schooling to the parent with the utility-weighted marginal benefit of additional earnings to the adult in period 2, as a result of schooling, and may be written as

$$(p^D + w_1^c)E_1[U^{'}(c_2^p)] = \gamma[U^{'}(c_2^a)f^{'}(D_1)] \tag{3}$$

From equation (3), it can be seen that the risk in second period parental income affects education in the first period through affecting the expected second period marginal utility of the parent. To isolate the effect of risk on investment in education, we follow Sandmo (1970) by defining a pure increase in dispersion as a combination of additive and multiplicative shifts in the distribution of parental income: the additive shift, θ, increases the mean whilst holding all other moments constant, and the multiplicative shift, $\delta > 1$, stretches the distribution on the right side of zero (assuming that income is non-negative).[6] We can thus think of expected parental income in period 2 as $E[\delta y_2^p + \theta]$ and for the increase in risk to be mean-preserving, it must be that the change in the expected value of future parental income is 0, i.e. $E[y_2^p d\delta + d\theta] = 0$.[7] We show in Appendix A.1 that the effect of a mean-preserving increase in risk on investment in education is

$$\left.\frac{\partial D_1}{\partial \delta}\right|_{\frac{d\theta}{d\delta} = -\xi} = \beta(p^D + w_1^c)U^{''}(c_1^{hh})E_1[U^{''}(c_2^p)(y_2^p - \xi)]/|H| \tag{4}$$

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[6]In what follows, derivations follow on Sandmo (1970) and are laid out in the appendix.

[7]This implies that $d\theta/d\delta = -E[y_2^p] = -\xi$.

where H denotes the (positive) Hessian. Under the assumption of decreasing absolute risk aversion, we show in Appendix A.1 that (4) is negative for all values of y_2^p: higher parental income risk leads to lower investment in human capital.

However, in formulating this model we have ruled out the situation in which the adult may make transfers towards the parent in the second period. Intergenerational transfers within the family are however a common phenomenon, particularly in LDCs, for a variety of reasons. For example, parents may invest in the child's human capital investment in order to appropriate some of the return in old-age, transfers may represent a repayment to parents for the investment, or they may be motivated purely by altruism on the part of the adult (Lillard and Willis, 1997). We therefore allow for the more realistic case of reverse altruism in our model, in the form of transfers (T) from the adult to the parent in period 2. We assume that these are increasing in the adult's education level, $T'(D_1) > 0$. It turns out that the adverse effects of risk on education may be mitigated in this set-up. Intuitively, this is because transfers, in providing a pecuniary benefit to the parent in period 2, reduce the overall net cost of education to the parent. More formally, we denote the degree of adult 'altruism' λ[8], where $0 < \lambda < 1$, and write adult utility as $U(c_2^a) = V(c_2^a) + \lambda E_1 U(c_2^p)$. The parent's problem is now to

$$\max_{c_1^{hh}, D_1} U(c_1^{hh}) + \beta(1 + \gamma\lambda)E_1 U(c_2^p) + \beta\gamma V(c_2^a) \tag{5}$$

The first-order condition for education (see Appendix A.2) becomes

$$(1 + \gamma\lambda)[(p^D + w_1^c) - T'(D_1)]E_1[U'(c_2^p)] = \gamma[V'(c_2^a)f'(D_1)] \tag{6}$$

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[8]We use the term 'altruism' liberally: as noted, adults may make transfers to parents for a number of reasons apart from altruism.

and the effect of a mean-preserving increase in risk on education is now

$$\frac{\partial D_1}{\partial \delta}\bigg|_{\frac{d\theta}{d\delta}=-\xi} = \beta(1+\gamma\lambda)[(p^D + w_1^c) - T'(D_1)].\underbrace{U''(c_1^{hh})E[U''(c_2^p)(y_2^p - \xi)]}_{A}/|H| \qquad (7)$$

We have seen already that $A < 0$, so the overall sign of (7) depends on the sign of $(p^D + w_1^c) - T'(D_1)$: the adverse effects of risk on education that we saw above would be mitigated, the higher the effects of education on transfers.[9]

In this section, we have proposed one set of conditions under which risk adversely affects investment in education, but when we relax the assumption that parents are the only altruistic agents in the model, we cannot rule out a mitigating or offsetting effect of risk on investment in education. This renders the theoretical effects of risk on education ambiguous, depending on the relative altruism of parents and their grown-up children towards each other. The relative importance of these assumptions is an empirical matter, and in the sections that follow, we go on to test empirically the effects of the amount of risk that the investor of the child's education faces or perceives, on investment in the child's human capital.

3.   Methodology

The starting point of the empirical analysis of the effects of risk on investment in education is to quantify the degree of ex-ante risk facing households, decomposed into household- and village-level components.

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[9]Note we have assumed for simplicity that transfers are exogenous. See Raut and Tran (1998); Baland and Robinson (2000), for analyses of intergenerational transfers and their effects on child labour.

We equate risk with income variability, and to quantify it, we start from the assumption that households base predictions of future volatility on the observed volatility of their past earnings streams. We observe five years of retrospective data regarding type of work, sector of work, hours and weeks worked, and monthly and weekly earnings from work. We use these data to obtain hourly wages of individuals for each of the past five years.[10]

We first estimate within-village log wage regressions using OLS on data pooled across individuals and years

$$\ln w_{h,v,t} = \beta X_{h,v,t} + \gamma_{v,t} + f_h + \epsilon_{h,v,t} \tag{8}$$

where $\ln w_{h,v,t}$ is the log hourly wage of household head h in village v in year t, $X_{h,v,t}$ contains a quadratic in the household head's age, $\gamma_{v,t}$ is a vector of time dummy variables that captures the component of the wage in period t that is common to all earners in village v, f_h captures the effects of time-invariant household head characteristics - that are known to the household - on wages, whether observed by the analyst (such as years of education) or not (such as ability), and $\epsilon_{h,v,t}$ is an iid error term that captures unobserved and unpredicted individual and village characteristics that affect wages.

From equation (8), $\widehat{\gamma}_{v,t}$ estimates the part of wages that is village-specific, for each year t; $\widehat{\epsilon}_{h,v,t}$ represents unexplained variation in the wage that is specific to household head h in village v, for each year t. We measure the variability of these over five years using the coefficient of variation, which we denote $\widehat{cv}_v$ and $\widehat{cv}_h$ for village and household respectively.[11]

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[10]Although it would be preferable to observe a longer panel of earnings data, we maintain that five years is sufficiently long to pick up fluctuations in earnings.

[11]The coefficient of variation is the standard deviation divided by the mean. Being scale-

The measure of earnings used in equation (8) is the hourly wage of the household head in his/her primary job.[12] This is because we want to measure variability of income that has *not* been affected by decisions that have been taken to smooth it. In this sense, we are assuming that the head is the main earner in the household and that his labour supply is exogenous to perceived risk.[13] This assumption is more plausible for earnings of the head than for total household earnings, as the latter may reflect households having adapted labour supply to avoid what would otherwise have been bad draws of income, thus being contaminated by ex-post labour supply. Note however that amongst household heads, around one quarter reports being self-employed with the help of "householders/temporary workers", so for these, net profits can not be entirely purged of ex-post labour adjustments.[14]

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invariant, it provides a comparable measure of variation for households that may have very different income levels, unlike the variance. Note that we make no attempt to measure the overall variance of wages: we simply measure the volatility of two components of wages, though note that each will contribute to the overall variance. We estimate the coefficient of variation of $\exp(\widehat{\gamma}_{v,t})$ and $\exp(\widehat{\epsilon}_{h,v,t})$, which relate to our underlying model for wage levels, $w_{h,v,t} = exp(\beta X_{h,v,t} + \gamma_{v,t} + f_h + \epsilon_{h,v,t})$. Note also that as a robustness exercise, we measure variability using the variance of log wages; we return to this in section 5.

[12]We assume that the current household head has been head for each of the past five years, and restrict the sample to household heads currently aged 25 through 65 to render this assumption more plausible.

[13]Note that the results are very similar when we use monthly earnings of the household head instead of hourly wages. This is reassuring, suggesting that our assumption of inelastic head labour supply is valid.

[14]Note that around another one quarter of household heads are self-employed but do not use family or hired labour, so their reported profits do not include any marginal products of

Measurement error in the dependent variable is of concern, particularly given the retrospective nature of the data (Deaton, 1997). It may be both classical and non-classical. We assume that any non-classical measurement error is fixed over time within the household, so that it is differenced out in estimating equation (8).[15] There is still a potential problem of classical measurement error, and as we will see in the next section, this is one reason for instrumenting these measures of variability.

3.1.   Identification

To estimate the effects of risk on investment in education, we start from the following equation

$$S_{i,v,t} = \alpha_0 + \alpha_1 \widehat{cv}_h + \alpha_2 \widehat{cv}_v + \alpha_3 W_{i,v,t} + \eta_{i,v,t} \tag{9}$$

where $S_{i,v,t}$ is a measure of human capital of individual (child) i in village v at time t, $\widehat{cv}_h$ and $\widehat{cv}_v$ are, respectively, estimates of household- and village-specific variability in wages, $W_{i,v,t}$ includes individual, household and village characteristics that affect investment in education, and $\eta_{i,v,t}$ captures the effects of unobserved characteristics on education.

One concern with estimating equation (9), already discussed above, is that both $\widehat{cv}_h$ and $\widehat{cv}_v$ are likely to be affected by measurement error. Our assumption that non-classical measurement error is fixed over time means that any noise in the measures is random. Such classical measurement error would render the coefficients α_1 and α_2 downward biased.

A second concern relates to the fact that both measures of wage variability may be correlated with the error term, $\eta_{i,v,t}$ in (9). To see this, note that $\widehat{cv}_h$ not only includes

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labour other than their own. The remainder of household heads are employees.

[15]This assumption is similar to that of Witoelar, 2005.

volatility that is due to unanticipated (risk) factors, but also that is due to unobserved yet predicted (non-risk) factors. The latter unobserved determinants of wage volatility may also have an effect on education, rendering α_1 a biased estimate of the effect of risk on education. Concerning the endogeneity of $\widehat{cv}_v$, it is not unrealistic to imagine that households that choose to live in relatively riskier villages have lower preferences for education, for example. Even though we control for many aspects of the village that are likely to be correlated with education choices, such as main use of land, cleanliness of the area, and productivity of the soil (see section 4), omitted variable bias must of course be of concern.

For both of these reasons, we use an Instrumental Variables methodology to identify the effects of risk on education. We argue in what follows that our instruments are valid in the sense of having no effect on education choices, except through their effects on risk. We will also provide evidence in section 5 from the first-stage regressions that they have predictive power in explaining the endogenous risk measures.

We instrument village-level risk using historical variation in rainfall across regions. Rainfall is the most important dimension of weather variation in Indonesia; moreover it exhibits important regional and seasonal differences (Levine and Yang, 2006). The key identifying assumption is that past rainfall variability is exogenous to recent education choices: the only way in which it has an effect is through impacting on the inherent riskiness of the village. Note that our rainfall data relate to the period between 1955 and 1978, and being so removed from the present, are unlikely to affect recent education choices. Moreover as we will see, none of the children comprising our sample were born before 1978. At the same time however, past weather realisations provide the same information about the deterministic component of weather regardless of how far in the past they are as long as weather is a stationary process (Wolpin, 1982), and we thus expect it to be related to the

riskiness of villages. A potential concern is that past rainfall may have led to disasters, for example causing damage to schools or bridges, thus directly affecting school attendance. However, as noted already, we use rainfall data over a period that is before the children in our sample were born. Moreover, we control for whether or not the village experienced a severe adverse shock - a flood, landslide or epidemic - in any of the periods 1980 through 1993, which may be correlated with past rainfall and also likely to directly affect education choices. Another point to note is that past rainfall may have affected the current value of assets of households, if assets were used to buffer consumption against weather vagaries. We thus control for the current (log) value of assets in the schooling equation.

Rainfall is also likely to have differential effects on incomes within villages, depending on how people earn their incomes (see for example Townsend, 1995). To instrument household risk, we thus use the interaction between the occupation of the household head and past rainfall variability, while controlling for occupation in the schooling equation. We do this in order to control for unobserved factors that are correlated both with occupation and education, such as preferences for child education. We do not, however, ascribe a causal interpretation to the parameter on occupation. The identifying assumption is that the relationship between occupation and schooling is invariant to past rainfall variability. This is consistent with excluding past rainfall variability from the schooling equation, and allowing it to have an effect on education only through income. The occupation classifications that we use are small farmer, medium farmer, large farmer, business owner, and private sector worker. Note that it is also plausible to expect adverse household shocks, such as the death of a householder, crop loss or business loss, to affect idiosyncratic household risk. However, it is difficult to argue that they have no direct effect on the stock of education and thus we do not use them as instruments at the household level. The average of these shocks at the village level is more likely to be exogenous for education choices however, although taking the average sweeps away some of the predictive power of

this variable. We see the use of these shocks as a more contentious instrument, and for this reason we present results both with and without it.

4. Data

The data used in the empirical analysis is the 1993 wave of the Indonesian Family Life Survey (IFLS). This is an ongoing longitudinal survey carried out by *Lembaga Demografi* of the University of Indonesia and RAND. It covers over 30,000 individuals in 7,224 households, spread across 13 provinces and 321 communities. Extensive community data can be linked to households.

In all that follows, we present the analysis for all areas pooled together, both urban and rural, as well as for rural areas separately. Estimating the results for rural areas separately is in line with most studies in this area (for example Rosenzweig 1988, Paxson 1992, Rosenzweig and Wolpin 1993), and it is for a number of reasons. First, rural incomes are low and uncertain compared to non-rural incomes, being determined to a large extent by weather conditions, due to the prevalence of farming as a source of income. Second, formal insurance markets are thin in rural areas, and there is a large literature on how households smooth consumption in the absence of formal insurance markets (see Case (1995) and references therein). Furthermore, there are acute constraints on borrowing in rural areas (Rosenzweig and Wolpin, 1993). This renders rural areas a suitable testing ground for our model, in the sense that if risk has any effect on education, it is more likely to be observed in rural areas.

The dependent variable is years of education of the child. This takes into account past temporary interruptions to schooling, which are one way of dealing with risk. To define a 'child', we exclude very young children whose formal work participation is likely to be low.

Surveys by Asra (1994, 1995) in Indonesia suggest that there is a considerable jump in work participation after age 10, so we exclude children below age 10. We also exclude individuals above 15.[16] Our final sample of children comprises 3,702 (1,959) 10 to 15 year olds across all (rural) areas. Approximately 80% (75%) of this sample is enrolled in school. The average number of years of education is 4.8 (4.5). Table 1 provides further mean values of household characteristics for our sample, all of which we control for in the analysis that follows. The mean values of the village-level characteristics that we control for are shown in Table 2. Note that we not only control for characteristics that directly affect schooling such as school supply, but also bank and insurance availability, and characteristics relating to soil productivity and the cleanliness of the village.

The rainfall data that we use to instrument risk are obtained from monthly reports on millimetres of rainfall recorded by the National Climatic Data Center at 504 weather stations throughout Indonesia. We use rainfall data between 1955 and 1978 and divide each year into two periods, corresponding to wet (April through September) and dry seasons (October through March).[17] Our set of instruments for aggregate village risk

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[16]The current minimum legal working age in Indonesia is 15, though the ILO Convention was only ratified in 1999. In our survey, just over 15% of 10-15 year olds report either working or looking for work.

[17]For each weather station, we drop years in which we do not have at least three rainfall observations per season. We keep only those weather stations for which we observe at least five years of rainfall data. This leaves us with rainfall data for 474 weather stations, and their latitude and longitude coordinates. We obtained special access to the latitude and longitude coordinates of the IFLS villages for this analysis, and we use these data to merge villages to their closest weather station. This leaves us with data on 62 exclusive weather stations. Of these, 48 villages are mapped to unique weather stations; most of the remaining

include (a) the (log) coefficient of variation of rainfall over time, for each of the two seasons, and (b) the (log) of the ratio of average rainfall in the wet season to average rainfall in the dry season. The former gives an indication as to variation in rainfall in the village *within* each season; the latter on the other hand is a measure of the spread of rainfall in the village *between* seasons. Note that this methodology differs from Paxson (1992) who uses the deviation of current rainfall from the average to instrument current income. However, as our endogenous regressor is the inherent riskiness of the village, which is a concept more closely related to volatility over time, we maintain that variation in rainfall over time is a more suitable instrument for this, and indeed in section 5 we provide empirical evidence to corroborate this claim. In Figure 1, we show the log of the ratio of average rainfall in the wet to the dry seasons, and the log standard deviation of rainfall over time, for both seasons, across our sample of villages. This Figure shows that there is substantial dispersion in rainfall across regions; moreover whilst average rainfall is higher in the wet season, it is also considerably more variable compared to the dry season.

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weather stations map to two villages; we are unable to match six of our sample of villages to weather stations.
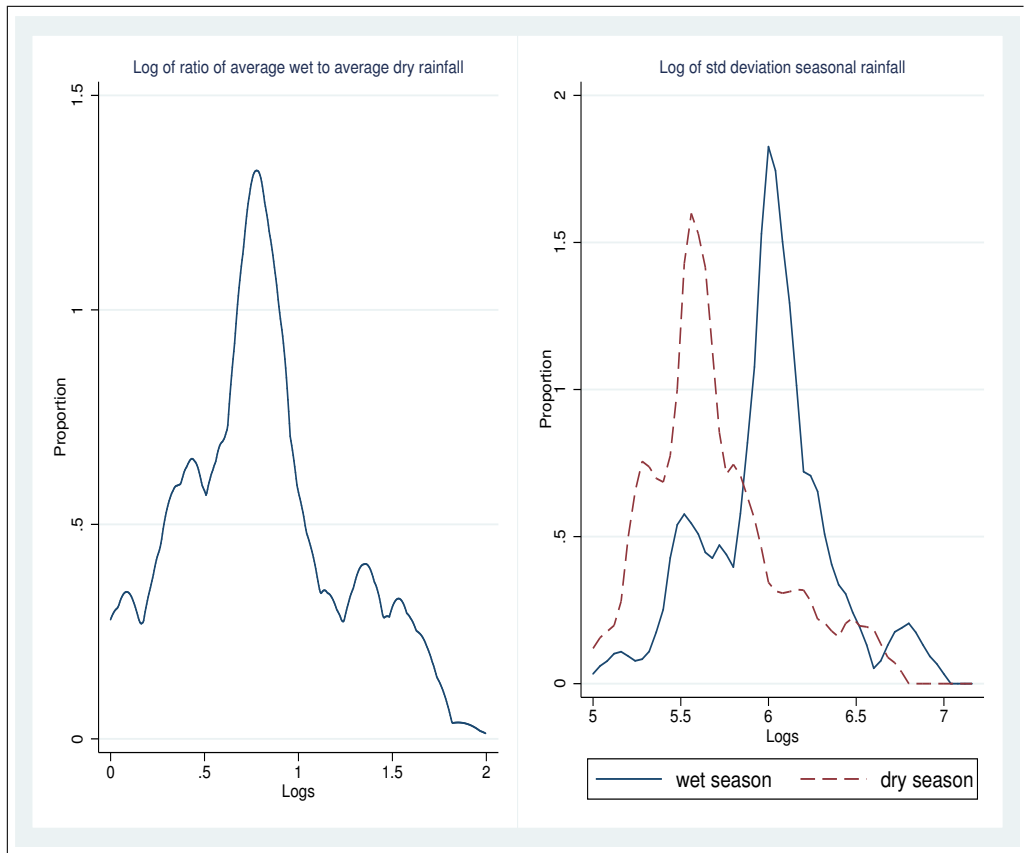
Fig. 1.— Kernel density estimates of log mean and log standard deviation of rainfall

5.   Results

The effects of risk on investment in education are estimated using Instrumental Variables, and so we consider first the output from the first stage regressions, for both household and village risk measures, in tables 3 and 4 respectively.

The upper panel of each table considers the relationship between the measures of risk, and observed household and/or village characteristics. For reasons discussed in section 4, we consider all areas together, as well as rural areas only. The lower panel of each table shows the effects of the instruments on the endogenous variables. It also reports the tests of the joint significance of the instruments.

Turning first to the reduced form estimates for household risk, we see that first, certain occupation types are associated with lower household-level risk: owning a business, being a private employee or being a medium farmer. Second, the number of adverse household shocks (death, crop loss or business loss) is associated with higher household level risk. Third, an unschooled mother is associated with decreased risk, whilst the opposite is the case for an unschooled father. If, as is likely, the father is the main earner, this is suggestive of a negative relationship between idiosyncratic income risk and education. In terms of the instruments, we see that the effects of rain volatility on household risk vary significantly depending on occupation type, particularly for the wet season measure. It is of course difficult to know *a priori* how the effects might be expected to vary for different occupations. It depends on factors such as the technologies adopted by different occupations, and the geographical position of different-sized farms. We see for example that small farmers face more household-level risk, the higher is the wet season rain variability; medium farmers on the other hand face lower risk in this situation.[18] The

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[18]It is difficult to know why this is the case, though one possible explanation may relate

interactions between occupation and dry season volatility are less important, though this would arise if for example the wet season is the greater determinant of agricultural output. Finally, note that the average number of household shocks in the village is positively and strongly associated with idiosyncratic risk.

Turning next to the reduced form estimates for village risk, shown in table 4, across both urban and rural areas, indicators of poverty in the village including low soil productivity, poor quality roofs and distance to a bank are associated with higher village risk. Other factors associated with higher village risk are farming as the main use of land, compared to settlement, and whether or not the village experienced a disaster in the period 1980 through 1993. The presence of insurance in the village, and irrigated ricefields, are associated with lower village risk. These associations with our measure of village risk are in line with expectations and are reassuring in that regard. The fact that the number of primary schools is associated with higher risk in rural areas is more puzzling, though one possible explanation is that it indicates limited access to child labour, one means of smoothing income. The instruments for aggregate village risk show that higher rainfall volatility is associated with significantly more risk, both in the wet and dry seasons. The ratio of average rainfall in the wet to the dry season is also associated with more village-level risk: this could be due to very high rainfall levels leading to flooding, for example.

We now go on to consider the effects of risk on years of education. Table 5 presents the results from estimating equation (9), in which the dependent variable is years of

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to the geographic positioning of farms. If, for example, small farms are situated close to rivers and are susceptible to more flooding, medium farmers might actually gain from the misfortune of small farmers in periods of high wet season rain.

education.[19] The left hand panel of the table shows the results across all areas, and the right hand panel restricts the estimation to rural areas. We show first OLS estimates, though as discussed in section 3.1, these must be treated with considerable caution, as our risk measures are not only noisy, but are also likely to be correlated with the error term in equation (9). We also show two sets of Instrumental Variable estimates, where in the second case we drop the average number of household shocks in the village from our set of instruments, again for reasons discussed in 3.1.

For all areas taken together, we see that neither household- nor village-level risk significantly affects years of education. For rural areas however, the story to emerge is quite different. From the OLS estimates, we can discern no significant effects of risk on years of education. However, when we instrument the measures of risk, the effects of village risk become negative and statistically significant at the 10% level. Moreover, the magnitude of the effects are large: an increase in village risk from the 10th percentile to the 90th percentile, would reduce years of education by 1.3 years. The effects of household risk turn positive, though not significantly so. In column (6), in which we drop the average number of household shocks at the village level from the set of instruments, the negative effect of village risk persists at the 10% level of significance.

We assess the robustness of the results to another measure of variability, the variance of the log of income.[20] To do this, we estimate the variance of each of the two components of

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[19]Note that repeat years of schooling are not counted as additional years of education. So the years of education measure captures any delays in the education process through having to repeat, through late enrolment, or through withdrawal for one (or more) year(s).

[20]This measure places greater weight on the lower end of the distribution than on the upper end, whereas the coefficient of variation weights all income levels equally.

log income that we use to capture village and household risk: $\widehat{\gamma}_{v,t}$ and $\widehat{\epsilon}_{h,v,t}$ respectively, from equation (8) in section 3.[21] The overall picture to emerge remains the same: we detect a negative effect of aggregate village risk on education in rural areas, which is significant at the 10% level. As before, we can not detect any effect of idiosyncratic household risk on education. These results are shown in Table 1A in Appendix A.3.

5.1. Interpretation of Results

The adverse effects of village-level risk on education in rural areas suggest that insurance against this type of risk is not complete. Similarly, the lack of any discernible effect of household-level risk is consistent with households already insuring themselves against this form of risk. This latter finding is consistent with the extensive evidence that markets work fairly well in Indonesia, particularly in Java (see, for example, Pitt and Rosenzweig (1986), Benjamin (1992)). However, this latter finding could also be due to there being a counteracting positive effect of household risk on education, which would arise in theory if parents were to use education to maximise future transfers from grown-up children (see section 2). This counteracting effect is less likely to be observed for village risk if parents believe that investment in education would not insure adult income (and thus future transfers) against fluctuations that are due to pervasive risk.

We have no way of knowing to what extent this transfer motive underlies our finding of no effect of household risk on education, but one useful exercise is to take a look at the importance of intra-family transfers in Indonesia. Work by Lillard and Willis (1997) and Frankenberg, Lillard and Willis (2002) for Malaysia and Indonesia respectively, finds that

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[21]As it is not our main interest here, we ignore any contribution to the variance of log wages that arises from any covariance between theses variables.

transfers from grown-up children to parents are substantial in these countries. Moreover, both studies find empirical evidence in support of the 'parental repayment' hypothesis, in other words parents investing in child education and children repaying them later on in old age.

However, altruistic heads of household might also care about transfers to other family members as well. Below we consider the relationship between transfers to *any* family members outside the household and the education level of the donor. Table 6 shows how education is related to the probability of giving transfers, as well as how education is related to the value of (positive) transfers. Conditioning on a range of background characteristics, we see that individuals with higher levels of schooling are more likely to give transfers, and moreover the amounts of these transfers are larger at higher levels of education.[22] There appears to be some evidence from this consistent with the notion that the transfer channel may be related to the observed effects of household risk on education choices.

A final couple of points are worth making. First, even though the presence of risk may affect schooling, it may act so as to delay the educational process, without having any adverse effect on the end stock of human capital. However, if withdrawal from school is an absorbing state, of which there is evidence (de Janvry et al, 2006), this has important implications for long-term poverty reduction. Second, even though the presence of risk may affect education, we can not infer the effects of risk on child labour on the basis of the evidence presented here. Indeed, there is evidence to suggest that the trade-off between schooling and work is not one-to-one (Ravallion and Wodon, 2000). Interesting future

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[22]Cameron and Cobb-Clark (2005) find no evidence of transfers being bring strongly related to children's education. However, their analysis is confined to a specific sample of elderly parents, aged 60 and over.

research questions include to what extent risk affects the end stock of human capital, as well as how it feeds through to work choices.

6. Conclusion

An important strand of the literature on education and work choices in LDCs has repeatedly documented reductions in education and/or increases in child labour as ex-post reactions to adverse shocks. However, to our knowledge, ours is the first paper to examine empirically the effects of *ex-ante* forms of risk on such investment decisions. In so doing, we developed a methodological framework to measure both idiosyncratic household and aggregate village components of ex-ante risk, in order to estimate the effects of each on human capital investment. This decomposition was motivated by the recurrent finding in the consumption and savings literature that idiosyncratic forms of risk are more easily diversified away by households than aggregate forms of risk.

We provided a simple theoretic framework to show how risk in parental income may affect investment in education. Our empirical focus was on the effects of ex-ante risk on investment in the education of children, thus distinguishing our work from the literature that considers the effect of ex-post income shocks on education choices. In analysing this question, we decomposed risk into village- and household-level components. To identify the effects of risk on education, we instrumented both measures using rainfall data that were obtained from data on weather stations that we mapped onto our household survey data.

Our findings point to a negative effect of aggregate village risk on the education of children. These findings suggest that children may fulfill an insurance role to protect household consumption against aggregate village risk, with detrimental effects on human capital accumulation. We find no evidence of idiosyncratic household risk affecting education. This is consistent with such risk being diversified by households without having to resort to the labour of their children. It is also consistent with parents increasing investment in education in response to risk, in order to elicit higher future transfers.

Further evidence is needed on this however, and understanding the links between risk, insurance and education, is important for the alleviation of long-term poverty. If households already have mechanisms in place to deal with certain types of risk, then providing insurance to low-income households might crowd out informal insurance arrangements. This paper points to the need for more research on this, in different LDC contexts, to inform policymakers.

REFERENCES

Asra, Abuzar. 1994. "Working Children in Bandung, Indonesia 1993." Jakarta, Central Bureau of Statistics and the International Labour Office.

Asra, Abuzar. 1995. "Working Children in Medan and Deli Serdang, North Sumatra, Indonesia." Jakarta, Central Bureau of Statistics and the International Labour Office.

Baland, Jean-Marie, and James A. Robinson. 2000. "Is Child Labor Inefficient?" *Journal of Political Economy* 108(4): 663-679.

Basu, K. 2006. "Gender and Say: A Model of Household Behaviour with Endogenously Determined Balance of Power." *Economic Journal* 116: 558-580.

Becker, Gary S. 1991. *A Treatise on the Family.* 2nd ed. Cambridge, MA: Harvard University Press.

Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti. 2005. "Child Labor and Agricultural Shocks." *Journal of Development Economics* 81(1): 80-96.

Benjamin, Dwayne. 1992. "Perspectives on Family and Fertility in Developing Countries." *Econometrica* 60(2): 287-322.

Cain, Mead. 1982. "Perspectives on Family and Fertility in Developing Countries." *Population Studies* 36(2): 159-175.

Cameron, L. and D. Cobb-Clark. 2005. "Do Coresidency with and Financial Transfers from Children Reduce the Need for Elderly Parents to Work in Developing Countries?", Discussion Paper, Centre for Economic Policy Research, The Australian National University.

Case, Anne. 1995. "Symposium on Consumption Smoothing in Developing Countries." *Journal of Economic Perspectives* 9(3): 81-82.

De Janvry, Alain., Frederico Finan, Elisabeth Sadoulet and Renos Vakis. 2006. "Can Conditional Cash Transfers Serve as Safety Nets in Keeping Children at School and from Working when Exposed to Shocks?" *Journal of Development Economics* 79(2): 349-373.

Deaton, Angus. 1997. "Analysis of Household Surveys: A Microeconometric Approach to Development Policy. Baltimore: John Hopkins University Press.

Frankenberg, Elizabeth, Lee Lillard, and Robert Willis. 2002 "Patterns of Intergenerational Transfers in Southeast Asia." *Journal of Marriage and the Family* 64 (3): 627-641.

Jacoby, Hanan, and Emmanuel Skoufias. 1997. "Risk, Financial Markets and Human Capital in a Developing Country." *Review of Economic Studies* 64(3): 311-335.

Kochar, Anjini. 1995. "Explaining Household Vulnerability to Idiosyncratic Income Shocks." *American Economic Review* 85(2), Papers and Proceedings: 159-164.

Levine, David I. and Dean Yang (2006), "A Note on the Impact of Local Rainfall on Rice Output in Indonesian Districts." Unpublished Manuscript, University of California, Berkeley, and University of Michigan.

Lillard, Lee A., and Robert J. Willis. 1997. "Motives for Intergenerational Transfers: Evidence from Malaysia." *Demography* 34(1): 115-134.

Morduch, Jonathan. 1995. "Income Smoothing and Consumption Smoothing." *Journal of Economic Perspectives* 9(3): 103-114.

Paxson, Christina. 1992. "Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand." *American Economic Review* 82(1): 15-33.

Pitt, Mark., and Mark Rosenzweig. 1986. "Agricultural Prices, Food Consumption and the Health and Productivity of Indonesian Farmers." In Inderjit Singh, Lyn Squire and John Strauss (eds.) *Agricultural Household Models: Extensions, Applications and Policy.* John Hopkins University Press (1986), 153-182.

Pörtner, Claus. 2001. "Children as Insurance." *Journal of Population Economics* 14(1): 119-136.

Ranjan, Priya. 2001. "Credit Constraints and the Phenomenon of Child Labor." *Journal of Development Economics* 64(1): 81-102.

Raut, Lakshmi K., and Lien H. Tran. 1998. "Motives for Investment in Human Capital of Children: Evidence from Indonesian Family Life Survey Data." Working paper, University of Hawaii-Manoa.

Ravallion, Martin, and Quentin Wodon. 2000. "Does Child Labour Displace Schooling? Evidence on Behavioural Responses to an Enrollment Subsidy." *Economic Journal* 110: C158-C175.

Rosenzweig, Mark. 1980. "Neoclassical Theory and the Optimizing Peasant: An Econometric Analysis of Market Family Labor Supply in a Developing Country." *Quarterly Journal of Economics* 94(1): 31-55.

Rosenzweig, Mark. 1988. "Risk, Implicit Contracts and the Family in Rural Areas of Low-Income Countries." *Economic Journal* 98: 1148-1170.

Rosenzweig, Mark, and Hans P. Binswanger. 1993. "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments." *Economic Journal* 103: 56-78.

Rosenzweig, Mark, and Oded Stark. 1989. "Consumption Smoothing, Migration and Marriage: Evidence from Rural India." *Journal of Political Economy* 97(4): 905-926.

Rosenzweig, Mark, and Kenneth Wolpin. 1993. "Credit Market Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India." *Journal of Political Economy* 101(2): 223-244.

Sandmo, Agnar. 1970. "The Effect of Uncertainty on Saving Decisions." *Review of Economic Studies*, 37(3): 353-360.

Sawada, Yasuyuki, and Michael Lokshin. 2001. "Household Schooling Decisions in Rural Pakistan", Policy Research Working Paper No, World Bank.

Thomas, Duncan, Kathleen Beegle, Elizabeth Frankenberg, Bondan Sikoki, John Strauss and Graciela Teruel. 2004. "Education during a Crisis." *Journal of Development Economics* 74(1): 53-86.

Townsend, Robert. 1994. "Risk and Insurance in Village India." *Econometrica* 62(3): 539-591.

Townsend, Robert. 1995. "Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low-Income Economies." *Journal of Economic Perspectives* 9(3): 83-102.

Udry, Christopher. 1994. "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria." *Review of Economic Studies* 61(3): 495-526.

Witoelar, Firman. 2005. "Inter-household Allocations within Extended Family: Evidence from the Indonesia Family Life Survey." Discussion Paper No.912, Yale University Economic Growth Center.

Wolpin, Kenneth. 1982. "A New Test of the Permanent Income Hypothesis: The Impact of Weather on the Income and Consumption of Farm Households in India."
International Economic Review 23(3): 583-594.

7.   Tables

Table 1: Mean Characteristics of Households

	All	**Rural**
Age of child	12.32 (1.74)	12.31 (1.72)
Male child	0.50 (0.50)	0.50 (0.50)
Child attending school	0.80 (0.39)	0.75 (0.43)
Child years of schooling	4.86 (2.07)	4.55 (1.98)
Unschooled mother	0.32 (0.47)	0.38 (0.48)
Unschooled father	0.29 (0.46)	0.34 (0.47)
Household size	6.12 (2.10)	5.92 (2.02)
Number of older siblings	1.14 (1.23)	1.00 (1.10)
Number of younger siblings	1.34 (1.30)	1.38 (1.33)
Household owns farm	0.41 (0.49)	0.63 (0.48)
Household owns business	0.39 (0.49	0.35 (0.48)
Head is private sector employee	0.30 (0.46)	0.20 (0.40)
Household owns assets	0.58 (0.49)	0.52 (0.50)
Log value of assets	6.93 (6.20)	5.99 (6.01)
Fraction of adults working	0.63 (0.30)	0.67 (0.30)
Householder suffered illness/died in past year	0.11 (0.31)	0.10 (0.30)
Islam	0.91 (0.29)	0.93 (0.26)
Protestant/Catholic	0.04 (0.20)	0.02 (0.14)
N	3,702	1,959

Notes: Standard deviations in parentheses.

Table 2: Mean Characteristics of Villages

	All	**Rural**
Number of households	1830 (2625)	931 (752)
Number of primary schools	3.86 (1.64)	3.61 (1.29)
Number of junior high schools	2.16 (1.25)	2.19 (1.29)
Number of senior high schools	1.43 (1.11)	1.29 (1.14)
Distance to nearest school (km)	2.14 (2.36)	3.04 (2.75)
Presence of bank	0.34 (0.48)	0.17 (0.38)
Distance to bank	5.00 (11.49)	8.57 (14.59)
Presence of insurance	0.10 (0.30)	0.05 (0.21)
Farming main use of land	0.64 (0.48)	0.93 (0.26)
Settlement main use of land	0.33 (0.47)	0.06 (0.23)
Village visibly polluted	0.21 (0.40)	0.08 (0.27)
Low quality roofs	0.31 (0.46)	0.31 (0.46)
Soil productivity high	0.19 (0.39)	0.18 (0.39)
Soil productivity average	0.50 (0.50)	0.55 (0.49)
Soil productivity low	0.30 (0.45)	0.25 (0.43)
Has irrigated ricefields	0.35 (0.47)	0.64 (0.48)
Rainfall mm 1991/1992	689 (1092)	550 (911)
Percentage reporting disaster 1980-1993	0.65 (0.48)	0.71 (0.45)

Notes: Standard deviations in parentheses.

Table 3: Reduced-Form Estimates, Household Risk

	All	**Rural**
Household size	0.002 (0.003)	0.001 (0.004)
Mother unschooled	-0.024 (0.009)**	-0.025 (0.013)*
Father unschooled	0.024 (0.011)**	0.016 (0.015)
Male household head	0.036 (0.014)**	0.032 (0.022)
Log value of assets	0.001 (0.002)	0.001 (0.004)
Owns assets	-0.021 (0.024)	0.002 (0.046)
Owns business	-0.095 (0.039)**	-0.127 (0.063)**
Owns small farm	0.105 (0.075)	0.126 (0.092)
Owns medium farm	-0.183 (0.079)**	-0.154 (0.097)
Owns large farm	-0.012 (0.056)	-0.021 (0.075)
Head is private sector employee	-0.115 (0.042)**	-0.147 (0.075)**
Islam	0.041 (0.014)**	0.044 (0.026)*
Fraction of adults working	0.012 (0.013)	0.018 (0.021)
Number of adverse shocks in past 5 years	0.015 (0.007)**	0.018 (0.009)*
Rain volatility wet season	0.031 (0.024)	0.057 (0.041)
Rain volatility dry season	0.077 (0.027)**	0.038 (0.045)
<u>Instruments</u>		
Rain volatility wet season*Small farm	0.083 (0.051)*	0.093 (0.063)
Rain volatility wet season*Medium farm	-0.109 (0.050)**	-0.088 (0.064)
Rain volatility wet season*Large farm	0.021 (0.037)	0.026 (0.050)
Rain volatility wet season*Business	-0.052 (0.027)*	-0.083 (0.042)**
Rain volatility wet season*Private sector	-0.038 (0.030)	-0.047 (0.051)

Table contd. overleaf

Table 3 contd. Reduced-Form Estimates, Household Risk

	All	Rural
Rain volatility dry season*Small farm	-0.033 (0.046)	-0.020 (0.056)
Rain volatility dry season*Medium farm	-0.015 (0.042)	-0.006 (0.052)
Rain volatility dry season*Large farm	-0.033 (0.030)	-0.039 (0.040)
Rain volatility dry season*Business	-0.036 (0.021)*	-0.046 (0.034)
Rain volatility dry season*Private sector	-0.022 (0.024)	-0.061 (0.042)
Ave # household adverse shocks in village	0.060 (0.017)**	0.103 (0.025)**
F-test P-value	0.000	0.000
Sample size	3,702	1,959

Notes: Omitted occupation is self-employed without owning farm or business. Standard errors, in parentheses, adjusted for clustering at the village level. ** statistically significant at the 5-percent level or less. * statistically significant at the 10-percent level.

Table 4: Reduced-Form Estimates, Village Risk

	All	**Rural**
Distance to nearest school	0.002 (0.001)**	0.003 (0.001)**
Insurance in village	-0.011 (0.004)**	-0.018 (0.009)**
Distance to bank	0.002 (0.001)**	0.002 (0.000)**
Productivity of soil low	0.005 (0.003)*	0.001 (0.005)
Farming main use of land	0.030 (0.008)**	0.035 (0.015)**
Poor quality roofs	0.009 (0.004)**	0.024 (0.006)**
Number of primary schools	0.000 (0.001)	0.008 (0.002)**
Has irrigated ricefields	-0.0120 (0.004)**	-0.014 (0.005)**
Village disaster 1980-1993	0.011 (0.003)**	0.008 (0.004)*
<u>Instruments</u>		
Rain volatility wet season	0.021 (0.008)**	0.0531 (0.013)**
Rain volatility dry season	0.034 (0.009)**	0.0236 (0.014)*
Ratio average rainfall: wet to dry season	0.041 (0.006)**	0.041 (0.009)**
F-test P-value	0.000	0.000

Notes: Standard errors, in parentheses, corrected for clustering at
the village level. ** statistically significant at the 5-percent level or less.
* statistically significant at the 10-percent level.

Table 5: Schooling Equations: Effects of Risk on Years of Education

	All			**Rural**		
	OLS	IV[a]	IV[b]	OLS	IV[a]	IV[b]
Household risk	-0.168	0.691	0.703	-0.140	1.521	0.980
	(0.130)	(2.226)	(2.201)	(0.162)	(2.289)	(2.064)
Village risk	-0.263	-0.558	-2.225	-0.567	-5.764	-6.533
	(0.501)	(2.743)	(3.827)	(0.696)	(3.155)*	(3.932)*
N		3,702			1,959	

Notes: Also control for household, individual and village characteristics shown in tables 1 and 2. Standard errors, in parentheses, corrected for clustering at the village level. ** statistically significant at the 5-percent level or less. * statistically significant at the 10-percent level.

[a] Instrument set includes average number of household adverse shocks in the village.

[b] Instrument set excludes average number of household adverse shocks in the village.

Table 6: Relationship between Donating Transfers and Donor's Education

	(1) Donate	(2) Log Amount
Elementary	0.067 (0.015)**	0.400 (0.069)**
Junior	0.092 (0.021)**	0.957 (0.087)**
Senior/College	0.158 (0.021)**	1.480 (0.090)**
r^2	0.032	0.150
N	11,571	6,055

Notes: Estimates in column (1) are marginal effects from a probit regression in which the dependent variable is 1 if individual makes transfers to a non co-resident family member, 0 otherwise. Estimates in column (2) are marginal effects from an OLS regression in which the dependent variable is the log amount of (positive) transfers. Also control for a range of donor's personal and household characteristics. Omitted education category is incomplete primary or no education. Standard errors, in parentheses, corrected for clustering at the village level. ** statistically significant at the 5-percent level or less.

A. Appendix

A.1. Parental Altruism

The first order conditions for consumption and education are respectively

$$\Psi_{c_1^{hh}} : U'(c_1^{hh}) - \beta E_1 U'(c_2^p) = 0 \tag{A1}$$

$$\Psi_{D_1} : \beta\gamma[U'(c_2^a)f'(D_1)] - \beta(p^D + w_1^c)E_1 U'(c_2^p) = 0 \tag{A2}$$

Effect of Parental Income Risk on D_1

$$\frac{\partial D_1}{\partial \delta}\Big|_{\frac{d\theta}{d\delta}=-\xi} = \frac{\begin{vmatrix} \Psi_{c_1^{hh}c_1^{hh}} & -\Psi_{c_1^{hh}\delta} \\ \Psi_{D_1 c_1^{hh}} & -\Psi_{D_1\delta} \end{vmatrix}}{|H|}$$

where H denotes the Hessian, $|H| > 0$ due to the second order condition for a maximum and

$$\Psi_{c_1^{hh}c_1^{hh}} : \left[U''(c_1^{hh}) + \beta E_1 U''(c_2^p)\right] dc_1^{hh}$$

$$\Psi_{D_1 c_1^{hh}} : \left[\beta(p^D + w_1^c)E_1 U''(c_2^p)\right] dc_1^{hh}$$

$$\Psi_{c_1^{hh}\delta} : -\beta E_1\left[U''(c_2^p)(y_2^p - \xi)\right] d\delta$$

$$\Psi_{D_1\delta} : -\beta(p^D + w_1^c)E_1\left[U''(c_2^p)(y_2^p - \xi)\right] d\delta$$

where we have substituted $\delta y_2^p + \theta$ for parental period 2 income and are evaluating the derivative keeping the mean of parental period 2 income constant.

$$\frac{\partial D_1}{\partial \delta}\Big|_{\frac{d\theta}{d\delta}=-\xi} = \frac{\begin{vmatrix} \left[U''(c_1^{hh}) + \beta E_1 U''(c_2^p)\right] & \beta E_1\left[U''(c_2^p)(y_2^p - \xi)\right] \\ \\ \left[\beta(p^D + w_1^c)E_1 U''(c_2^p)\right] & \beta(p^D + w_1^c)E_1\left[U''(c_2^p)(y_2^p - \xi)\right] \end{vmatrix}}{|H|}$$

$$= \beta(p^D + w_1^c)U''(c_1^{hh})E_1[U''(c_2^p)(y_2^p - \xi)]dc_1^{hh}d\delta/|H| \tag{A3}$$

Risk aversion implies that $U''(c_1^{hh}) < 0$. The sign of $\dfrac{\partial D_1}{\partial \delta}|_{\frac{d\theta}{d\delta}=-\xi}$ is the opposite sign of $E_1[U''(c_2^p)(y_2^p - \xi)]$. The sign of $E_1[U''(c_2^p)(y_2^p - \xi)]$ is determined below for all values of y_2^p.

$\boxed{y_2^p \geq \xi}$

Under the assumption that risk aversion $-\frac{U''(c_2^p)}{U'(c_2^p)}$ is decreasing in c_2^p

$$-\frac{U''(c_2^p)}{U'(c_2^p)} \leq \left(-\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi \quad \text{if} \quad y_2^p \geq \xi \tag{A4}$$

$$U'(c_2^p)(y_2^p - \xi) \geq 0 \quad \text{if} \quad y_2^p \geq \xi \tag{A5}$$

Multiply (A4) by (A5) $\Rightarrow U''(c_2^p)(y_2^p - \xi) \geq -\left(-\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi U'(c_2^p)(y_2^p - \xi)$

Take expected values on both sides

$$\Rightarrow E_1[U''(c_2^p)(y_2^p - \xi)] \geq -\left(-\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi E_1[U'(c_2^p)(y_2^p - \xi)] \tag{A6}$$

To prove that LHS ≥ 0, it is sufficient to show that RHS ≥ 0. This amounts to showing that $E_1[U'(c_2^p)(y_2^p - \xi)] \leq 0$

Since $U''(c_2^p) < 0$,

$$U'(c_2^p) \leq \left(U'(c_2^p)\right)_\xi \text{ if } y_2^p \geq \xi$$

Also,

$$y_2^p - \xi \geq 0 \text{ if } y_2^p \geq \xi$$

$\Rightarrow U'(c_2^p)(y_2^p - \xi) \leq (U'(c_2^p))_\xi(y_2^p - \xi)$

Take expected values

$\Rightarrow E_1[U'(c_2^p)(y_2^p - \xi)] \leq (U'(c_2^p))_\xi E_1(y_2^p - \xi) = 0$

$\Rightarrow E_1[U''(c_2^p)(y_2^p - \xi)] \geq 0 \quad \text{from} \quad (A6)$

$\boxed{y_2^p \leq \xi}$

Because risk aversion is decreasing in c_2^p, it must be that

$$-\frac{U''(c_2^p)}{U'(c_2^p)} \geq \left(-\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi \text{ if } y_2^p \leq \xi \tag{A7}$$

Also

$$U'(c_2^p)(y_2^p - \xi) \leq 0 \text{ if } y_2^p \leq \xi \tag{A8}$$

Multiply (A7) by (A8)

$$\Rightarrow U''(c_2^p)(y_2^p - \xi) \geq \left(\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi U'(c_2^p)(y_2^p - \xi) \tag{A9}$$

$\Rightarrow E_1[U''(c_2^p)(y_2^p - \xi)] \geq \left(\frac{U''(c_2^p)}{U'(c_2^p)}\right)_\xi E_1[U'(c_2^p)(y_2^p - \xi)]$

To prove that LHS ≥ 0, it is sufficient to show that RHS ≥ 0. So it must be shown that
$E_1[U'(c_2^p)(y_2^p - \xi)] \leq 0$

$$U'(c_2^p) \geq \left(U'(c_2^p)\right)_\xi \text{ if } y_2^p \leq \xi$$

Also

$$y_2^p - \xi \leq 0 \text{ if } y_2^p \leq \xi$$

$\Rightarrow U'(c_2^p)(y_2^p - \xi) \leq (U'(c_2^p))_\xi(y_2^p - \xi)$

Take expected values

$\Rightarrow E_1[U'(c_2^p)(y_2^p - \xi)] \leq (U'(c_2^p))_\xi E_1(y_2^p - \xi) = 0$

$\Rightarrow E_1[U''(c_2^p)(y_2^p - \xi)] \geq 0 \quad \text{from} \quad (A9)$

A.2. Parental and Adult Altruism

The first order condition for education is

$$\Psi_{D_1} : \beta\gamma[U'(c_2^a)f'(D_1)] - \beta(1+\gamma\lambda)(p^D + w_1^c - T')E_1U'(c_2^p) = 0 \qquad (A10)$$

and

$$\Psi_{D_1 c_1^{hh}} : \left[\beta(1+\gamma\lambda)(p^D + w_1^c - T')E_1U''(c_2^p)\right]dc_1^{hh}$$

$$\Psi_{D_1 \delta} : -\beta(1+\gamma\lambda)(p^D + w_1^c - T')E_1\left[U''(c_2^p)(y_2^p - \xi)\right]d\delta$$

where we have substituted $\delta y_2^p + \theta$ for parental period 2 income and are evaluating the derivative keeping the mean of parental period 2 income constant.

$$\frac{\partial D_1}{\partial \delta}\Big|_{\frac{d\theta}{d\delta}=-\xi} =$$

$$\frac{\begin{vmatrix} \left[U''(c_1^{hh}) + \beta E_1 U''(c_2^p)\right] & \beta E_1\left[U''(c_2^p)(y_2^p - \xi)\right] \\ \\ \left[1+\gamma\lambda)(p^D + w_1^c - T')E_1U''(c_2^p)\right] & \beta(1+\gamma\lambda)(p^D + w_1^c - T')E_1\left[U''(c_2^p)(y_2^p - \xi)\right] \end{vmatrix}}{|H|}$$

$$= \beta(1+\gamma\lambda)(p^D + w_1^c - T')U''(c_1^{hh})E_1[U''(c_2^p)(y_2^p - \xi)]dc_1^{hh}d\delta/|H|$$

A.3. Robustness

Table 1A: Effects of Risk on Years of Education.

Sensitivity Analysis.

	All		Rural	
	IV^a	IV^b	IV^a	IV^b
Household risk	0.385	0.409	0.241	0.263
	(0.455)	(0.471)	(0.412)	(0.390)
Village risk	-2.424	-5.022	-8.010	-7.831
	(4.164)	(4.964)	(4.710)*	(4.694)*
N	3,702		1,959	

Notes: See notes to Table 5 in main text.