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Risk and Schooling Decisions in Rural Madagascar: a Panel Data Analysis

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RISK AND SCHOOLING DECISIONS IN RURAL MADAGASCAR: A PANEL DATA ANALYSIS[1]

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ABSTRACT

Most households in rural Madagascar are engaged in agriculture and derive a large share of their income from the production of food or cash crops and from animal husbandry. However, agricultural yields can be extremely volatile due to weather conditions, pests, insects, rodents and other calamities. As a result, households record large fluctuations in their incomes that must be dealt with. Since the usual consumption-smoothing market mechanisms are quite limited in the Malagasy context, households need to rely on nonmarket mechanisms or to adopt multi-faceted strategies to cope with risk. In this paper, we examine the possibility that parents obtain informal income insurance by letting their children work. We test this hypothesis by examining the relationship between household income shocks and human capital investment in children. In particular, we investigate whether children's propensity to join school and to drop out of school responds to transient shocks. We also investigate issues such as gender and intrahousehold resource allocation.

Key Words: Schooling decisions; Transitory shocks; Risk-coping strategies.

RESUME

La plupart des ménages ruraux malgaches tirent l'essentiel de leurs revenus de l'agriculture et sont exposés à un fort degré d'incertitude en raison de la fréquence et de l'intensité des aléas frappant les champs de culture ou les troupeaux. En l'absence de marchés du crédit ou de l'assurance, des moyens alternatifs pour éliminer ou atténuer les conséquences défavorables de cette incertitude doivent être trouvés par les ménages. Dans cet article, nous envisageons la possibilité que la mise au travail des enfants constitue un mécanisme de gestion des risques. Afin de tester cette hypothèse, nous examinons les déterminants de la scolarisation en cycle primaire d'un échantillon d'enfants issus de ménages ruraux. Nous examinons notamment le rôle des chocs de revenu subis par les ménages sur les probabilités d'entrée (dans) et de sortie hors de l'école de leurs membres en âge d'être scolarisés, en portant une attention particulière aux questions de genre et d'allocation intra-ménage des ressources. Les résultats indiquent que les chocs transitoires de revenu ont un impact significatif sur la probabilité de sortie de l'école mais pas sur la probabilité d'entrer à l'école. Cela suggère que la déscolarisation des enfants les plus âgés constitue un mécanisme de gestion du risque pour les ménages ruraux.

Mots-clés : Décision de scolarisation ; Chocs transitoires ; Stratégies de gestion des risques

JEL Code : D91; I21; J24; O55.

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1. Introduction

Most households in rural Madagascar are engaged in agriculture and derive a large share of their income from the production of food or cash crops and from animal husbandry. However, agricultural yields can be extremely volatile due to weather conditions, pests, insects, rodents and other calamities. As a result, households record large fluctuations in their incomes that must be dealt with. Since the usual consumption-smoothing market mechanisms are quite limited in the Malagasy context, households need to rely on nonmarket mechanisms or to adopt multi-faceted strategies to cope with risk. Such coping strategies include drawing down liquid assets, liquidating productive assets, borrowing from formal or informal lenders, increasing market hours-of-work, etc. In this paper, we examine the possibility that parents obtain an informal income insurance by letting their children work. Because our data set does not provide us with detailed information on child labor, we test this hypothesis by examining the relationship between household income shocks and human capital investment in children. In particular, we investigate whether children's propensity to join school and to drop out of school responds to transient shocks[1]. We also investigate issues such as gender and intrahousehold resource allocation.

Almost no studies except Jacoby & Skoufias (1997) for India, Jensen (2000) for Côte d'Ivoire and Sawada (2003) for Pakistan have empirically explored the connection between financial market imperfections and human capital investment. Yet this question is important for at least two reasons. First, it can shed a new light on what determines child labor and may consequently suggest new possible remedies for it. Indeed, if households' incapacity to handle

[1] It is not obvious, however, that for children school and work compete for time. Increasing hours of work may simply crowd out leisure time and have no effect on school attendance.

temporary income shocks appears to be a more important determinant of school attendance than poverty, it suggests that programs aimed at helping poor parents handle emergencies may be more effective in keeping poor children in school than program aiming either at reducing poverty itself or at reducing school costs for the poor as a whole. Second, examining this question can clarify one of the mechanisms through which transient poverty causes chronic poverty.

Using five rounds of household panel data from four regions of Madagascar, we find that transitory income affects children's school dropout behaviors significantly. Our analysis also suggests that parents in our sample favor girls in terms of education. Although this last result might appear surprising, it is actually in line with existing studies on education in Madagascar which generally find a "negative" gender gap when focusing on school enrollment rates (see e.g. Cogneau, Dumont, Glick, Razafindrakoto, Razafindravonona, Randretsa & Roubaud 2003). Lastly, we find weak evidence of resource competition among siblings.

The paper is organized as follows. We begin by briefly reviewing the literature on the use of child labor as a form of self-insurance. The empirical strategy is then outlined in section 3. In section 4, we describe our data. In section 5, we present the results. Section 6 concludes the paper and suggests directions for future work.

2. Risk and Schooling Decisions: a Review

If the role of family income in determining child school attendance, enrollment or attainment has been widely explored in the literature, the impact of income fluctuations on the dynamics of school attendance and/or on child labor is comparatively a neglected issue even though recent empirical studies have been partially filling the gap for the last ten years. Using the

ICRISAT data set on a panel of Indian rural households, Jacoby & Skoufias (1997) examine whether fluctuations in family income affect school attendance in the face of financial market incompleteness. They find that child school attendance does decline when poor households are hit by a shock. They also find that school attendance is more responsive to aggregate than to idiosyncratic shocks. Using data from the Côte d'Ivoire Living Standard Survey (CLSS), Jensen (2000) find that school enrollment rates declined by between one-third and one-half in regions that had adverse weather shocks in 1986 and 1987. Sawada (2003) examines the role of permanent and transitory income changes in educational investments using household panel data from rural Pakistan. Unlike Jacoby & Skoufias (1997), which analyzes the variability of school attendance, the focus is on school entry and dropout behaviors. Results suggest that transitory income affects children's school entry and dropout behaviors significantly and that schooling response to transitory income is consistently larger for daughters than sons. In a forthcoming paper using a panel data set in one region of Tanzania, Beegle, Dehejia & Gatti (2006) find that transitory income shocks lead to increases in child labor and to decreases in school attendance. They also find that households with assets are able to offset approximatively 80% of these shocks.

The question of whether volatile income in an environment of imperfect insurance or capital markets leads to lower investments in education has also been empirically investigated in urban areas. Using longitudinal employment survey data collected in metropolitan Brazil, Duryea, Lam & Levison (2003) find that an unemployment shock to the household head significantly increases the probability that a child enters the labor force and decreases the probability that she advances in school. Their estimates suggest that these effects can be large, with increase of as much as 60% in the probability of entering employment for 16 year-old girls. By contrast, Parker & Skoufias (2006) find that, in urban Mexico, time devoted by boys and girls to schooling is unaffected by labor market shocks. However, when examining the effect of the same shocks on children's school attendance in the next school year, the authors find a significant decrease in the probability that the children will continue. The authors also find evidence of more effective efforts to protect family investments on children's human capital for boys than girls.

Finally, several studies have examined the role of cash transfers on households' school enrollment and child work decision (see e.g. Skoufias & Parker 2001, Bourguignon, Ferreira & Leite 2003, Schultz 2004, de Janvry, Finan & Sadoulet 2006). In a forthcoming paper, de Janvry et al. (2006) examine whether children who benefit from Progresa conditional transfers in rural Mexico are protected from the impacts of shocks on school enrollment and work. They find that shocks such as unemployment or illness of the household head have large effects in taking children out of school and that because of strong state dependence, children who dropped out of school are less likely to subsequently re-enroll. They also find that the Progresa transfers completely protect children from the impact of shocks on school enrollment.

3. Empirical Strategy

Our goal is to estimate the extent to which school attendance responds to income fluctuations under missing or incomplete credit and/or insurance markets. We do so in two steps. We first derive an estimate of agricultural income shocks. We then regress schooling decisions (either to enter into school or to dropout of school) on this estimate and other explanatory variables such as child age.

3.1. *The first step*

We adopt Paxson (1992)'s approach to construct our measure of transitory agriculture income shocks by using the following regression equation:

$$Y_{irt} = \beta_0 + X_{it}^P \beta_1 + X_{it}^T \beta_2 + X_{rt}^T \beta_3 + (X_{it}^P \bigotimes X_{rt}^T)\beta_4 + \lambda_i + \theta_t + \varepsilon_{it}^T$$

where Y_{irt} denotes agricultural income accruing to household i in region r in year t. X_{it}^P is a vector of physical and human assets - such as the demographic structure of the household, detailed information on its land holdings and their quality, and physical assets; X_{it}^T is a vector of household-specific shock variables and X_{rt}^T is a set of region-specific shocks - such as rainfall - that affect transitory income. $X_{it}^P \bigotimes X_{rt}^T$ is a cross-product term that is included in recognition of the fact that the effect of unexpected rainfall on agricultural income depends on farm characteristics. Unobservable determinants of the permanent component of income are captured by the household fixed effect λ_i. Finally, θ_t is a time-specific fixed effect and ε_{irt} is a random error term. The fitted value of the third and fifth terms in the right-hand side, i.e., the fitted value of $X_{it}^T \beta_2 + (X_{it}^P \bigotimes X_{rt}^T)\beta_4$, provides a consistent estimate of a component of income for household i in period t that is transitory and could not be anticipated. It is this measure of transitory income that will be used as a source of variation in our subsequent specifications.

Our specification differs in three ways from Paxson (1992)'s. First, in Paxson's income equation, rainfall is not interacted with farm characteristics so that heterogeneity in households' land holdings is not accounted for in her measure of transitory income shocks. Second, Paxson uses cross-sectional data on farm household income and cannot control for unobserved household fixed effect. Third, Paxson ignores other possible types of shock (e.g., pests, thefts and rodents) that can potentially strongly (and unexpectedly) influence agricultural income.

3.2. *The second step*

The longitudinal structure of our data set allows us to classify the sampled children into one of the following mutually exclusive categories: (i) no schooling; (ii) entrant; (iii) continuing schooling and (iv) dropout. We follow Sawada (2003)'s approach and construct simple models of binary dependent variables related to two sequential schooling decisions: whether to enter into school and whether to drop out from school. We define two binary variables as follows:

$$\begin{aligned}
\mathrm{ENT}_{it} &= 1 \text{ if child enters school at time } t \\
&= 0 \text{ if child does not enter school at time } t \\
\mathrm{DRP}_{it} &= 1 \text{ if child drops out of school at time } t \\
&= 0 \text{ if child stays in school at time } t
\end{aligned}$$

The entrant model is conditional on the sample of children without previous schooling ($S^*_{it-1} \leq 0$), i.e., children belonging to categories (i) or (ii), while the dropout model is conditional on the sample of children with some schooling ($S^*_{it-1} > 0$), i.e., children belonging to categories (iii) or (iv).

The relevant conditional probabilities can be written as:

$$
\begin{aligned}
P(\text{ENT}_{it}=0) &= P\left(S^*_{it}\le 0 \mid S^*_{it-1}\le 0\right) = 1-F(\alpha_h + X_{it}\pi) && (3.1)\\
P(\text{ENT}_{it}=1) &= P\left(S^*_{it}> 0 \mid S^*_{it-1}\le 0\right) = F(\alpha_h + X_{it}\pi) && (3.2)\\
P(\text{DRP}_{it}=0) &= P\left(S^*_{it}> 0 \mid S^*_{it-1}> 0\right) = 1-F(\gamma_h + X_{it}\beta) && (3.3)\\
P(\text{DRP}_{it}=1) &= P\left(S^*_{it}\le 0 \mid S^*_{it-1}> 0\right) = F(\gamma_h + X_{it}\beta) && (3.4)
\end{aligned}
$$

where α_h and γ_h represent household specific fixed effects and X is a vector of independent variables including the transient income estimate constructed in step 1. We estimate these models as discrete response models with household fixed effects assuming that $F(\bullet)$ is a logistic distribution function.

4. Data and Descriptive Statistics

The data come from a survey jointly administered by Madagascar's national statistical institute (INSTAT) and the Institut de Recherche pour le Developpement (IRD) through the Project MADIO (see e.g. Droy, Ratovoarinony & Roubaud 2000). The survey has been conducted every year since 1995 in four distinct regions of the country. These regions differ in terms of soil quality, annual rainfall pattern, and population densities. They were chosen because each of them illustrates at least one important issue in terms of agricultural development. In the first round, approximately 500 households were randomly chosen in each region from an exhaustive list. These households were surveyed again every year, and households that had moved or were unwilling to be surveyed were replaced by new households with similar characteristics from the same region. The resulting sample consists of 5,046 households surveyed over the period 1995 to 2002. Unfortunately, not all survey rounds can be used for our study since some of the questions related to education that we use to construct our in- and out-of-school variables were not asked in 1996. Furthermore, only households with school-aged children are included in our sample. As a result, the sample we use consists of about 2,200 households surveyed at least twice over the period 1997 to 2002.

The data set has several features that make it particularly appropriate for the proposed analysis. First, it provides rich and reliable information on production, assets and personal characteristics of all household members including their school enrollment status. It also includes detailed information on crop losses in each of the six rounds.

An important issue in the empirical analysis of panel data is the extent of sample attrition. Even though there is no necessary relationship between the size of sample loss from attrition and the existence or magnitude of attrition bias, we need to explore the determinants of panel attrition and investigate whether it is selectively related to some variables of interest. In particular, given the focus of the paper, namely the occurence of shocks and their impact on schooling decisions, we need to examine whether the likelihood of household or individual attrition is correlated with shocks. In order to do so, we conduct a dynamic attrition analysis by estimating attrition hazards, i.e., probabilities of exiting the sample in the current period conditional on being in the sample in the previous period, as a function of all the lagged variables of interest. The model to be estimated is as follows:probabilities of exiting the sample in the current period conditional on being in the sample in the previous period

$$A_{it} = f\left(shocks_{t-1}\right) + X_{it-1}\theta + v_{it} \tag{4.1}$$

where the outcome variable A_{it} equals 1 if the individual attrites at time t, conditional on still being respondent at time $t-1$ (0 otherwise). It is a function of past shocks such as income shocks or demographic shocks. The vector X_{it-1} are lagged individual characteristics, with coefficient vector θ, and v_{it} is an error term. In the empirical analysis, we also include year dummies interacted with village dummies. Estimates are shown in Table 1. They reveal that attrition propensity is not affected by our measures of shocks, indicating that attrition bias should not be a concern in our analysis. We likewise find that these variables are not significant predictors of entry into the sample.[2]

In the first part of the empirical section, the dependent variable is a measure of income that includes both cash and imputed value for in-kind income from various sources (farm production which includes food and cash crops and animal husbandry; non farm production which includes forestry, handicrafts, fishing and small trade; earnings from wage work; and rents from land). Turning to our measures of income shocks, different types and levels of risk are considered. First, we use household level information on negative shocks resulting from pests, rodents, birds or locusts. For each type of crop (rice, maize, roots and tubers), households were asked to give a score of losses on their fields as well as on their stocks in each survey round. Shock scores vary between 0 (no loss) and 3 (harvest reduced to nothing). We use this information to measure transitory household-specific shocks. Second, region-specific risk, which affects all households in a given region, is captured by rainfall data. Both the standard deviation of rainfall from its long-term average and its squared are included in the regression. Rainfall data come from the NASA/GSFC Laboratory for Atmospheres as a contribution to the GPCP, an international research project of the World Meteorological Organization's Global Energy and

[2] Results are not reported but are available upon request.

Water Exchange program.[3] Third, in order to introduce some heterogeneity in household-level sensitivity to climatic shocks, we introduce the cross-product of soil types and rainfall deviation in rice-growing observatories (rice being the main food crop in Madagascar). Some descriptive statististics on household-specific shocks are given in Tables 2, 3a and 3b. Although their economic and agroclimatic environment differ, all households in the sample face relatively high levels of income risk. As highlighted by Table 2, the frequency of shocks over time is particularly high in rice fields since nearly 33% of the 942 households that were interviewed in all five rounds experienced shocks in their rice fields in four or five rounds. This proportion falls to 7.4% when shocks in maize fields are considered. As pointed out by Beegle et al. (2006), the high frequency of shocks in rice fields raises the concern that our shock measures might pick up unobserved household characteristics rather than identifying an exogenous source of variation in income. The inclusion of household fixed effects in all subsequent specifications will at least partially control for this. Tables 3a and 3b report the magnitude of shocks in rice and cassava fields respectively in each survey round. While complete crop destruction is uncommon, shocks appear to be substantial in magnitude : 20% of households on average report heavy losses in their ricefields in each survey round. Moreover, shocks experienced by households in their fields appear to be not purely idiosyncratic.

In the second part of the empirical section, the construction of the dependent variables of the entry-drop out models is made possible by using information on schooling attendance from the panel of individuals. Transitions in and out of school are then coded as described in section 3. Figures 1 and 2 show the distribution of both dependent variables by age and gender. Not

[3] Detailed information is available at http://precip.gsfc.nasa.gov/ . Monthly ground measures on rainfall are also available for each observatory but are missing for years 2001 and 2002. Correlations between these measures and those provided by the NASA vary between 0.85 and 0.94 depending on the observatory under concern.

surprisingly, the profiles indicate important variations with age: entry probability increases steeply between age 4 to 7 - when it reaches a high of 35% for boys and 40% for girls - and decreases afterwards; drop-out probability is lower than 10% under 12 and increases to reach 40% at age 18. Figure 3 confirms that the proportion of children involved in domestic and agricultural labor increases with age.

In order to give some ground to the assumption that transitory shocks and schooling decisions are connected, Table 4 reports the proportions of sample children who dropped out from school in each observatory and each year, depending on whether their household experienced a shock or not. No clear picture emerges from it. The figures reveal higher probabilities of dropping out from school for children belonging to households having reported shocks in their ricefields in two observatories out of three (Antalaha and Marovoay). But shocks in maize fields are paradoxically associated with lower probabilities of dropping out from school in three observatories out of four.

Table 5 reports pair wise correlations of schooling rates at the household level, per capita income mean and deviation, and rainfall deviation. While schooling rates appear to be strongly correlates with mean per capita income in all observatories, they are significantly correlated with income and rainfall deviation only in Antalaha and Tuléar. These results suggest that schooling rates may be responsive to both idiosyncratic and common shocks at least for a subset of households. This will be investigated more rigorously in the following section.

5. Empirical Results

In addition to the measures of shocks described in the previous section, the vector of regressors in the income regressions includes rice field area, the percentage of irrigated land, the composition of the livestock owned by the household and the number of male and female elders, adults, young adults, children aged between five and fifteen and children who are younger than five. For the observatory of Antalaha, where a large share of cultivated land is devoted to vanilla, the vector of regressors also includes variables related to the number of vanilla trees owned by each household. Summary statistics by observatory are provided in Table 6.

Table 7 reports the fixed effects estimates of the determinants of total income for each observatory (Antalaha, Antsirabe, Marovoay and Tulear). For most of the variables, coefficients are in line with expectations. Rice land area is found to significantly raise total income and so does the percentage of irrigated land. Family labor is also found to give positive returns. For transitory shock variables, the deviation of annual rainfall from its long-term average has a significant impact on income in all observatories. However, the effect is positive in only three observatories (Antalaha, Antsirabe and Tuléar) and negative for Marovoay. This last result probably stems from the fact that most rice fields in Marovoay are irrigated and that heavy rains could be detrimental to the irrigation infrastructure or to the capacity of households to properly drain their fields. The effet of rainfall on income is found to be convex rather than concave in all observatories but Marovoay. There is also substantial variability across soil types in the responsiveness of crop income to rainfall. Most of the other transitory shock variables are found to negatively affect crop income, even though coefficients are not always significant. Rice being by far the predominant culture in Marovoay, a negative shock in rice fields (interacted with area planted in rice) is found to significantly decrease crop income. The same is true in Antalaha and Tulear for maize production. Last, the null hypothesis that there are no household fixed effects is strongly rejected in all income regressions.

Variables used in the conditional logit estimations are described in Table 8. Next to the gender indicator variable, child-specific variables include child age (not reported), child's relation to head and rank among brothers and sisters, as well as the number of older and younger siblings by gender. In addition to household fixed effects, which capture both invariant and unobservable characteristics of the households, we also introduce village-year fixed effects to control for village-level shocks or changes in the local availability of schools.

Tables 9 and 10 report the estimated coefficients of the entrant and dropout models respectively. Two alternative specifications are presented. In the first one, we use the transitory income shock variable derived from the income regressions described above. In the second one, in order to check for robustness, we use a more reduced-form specification where shocks incurred by households in their ricefields are introduced directly in the equation. In order to account for the relative importance of rice in households' income-generating activities, this shock variable is interacted with the size of land cultivated in rice. Unanticipated demographic events are also accounted for through the introduction of a variable measuring the number of elderly household members exiting the sample from one year to another.[4]

In the entrant model, the coefficient of transitory income is positive but not significant, implying that neither a positive income shock nor a negative one influences the probability of entrance to school. On the other hand, the death (or moving-out) of an elderly household member in the last 12 months is found to significantly decrease the probability of entrance to school. Turning to child-specific variables, girls are found to have a consistently higher probability to enter school than boys, and household heads appear to favour their own offsprings.

[4]Unfortunately, the survey questionnaire does not allow to identify the causes of individual attrition. Our assumption here is that death is the cause of attrition for most elderly members, even though some of them may have decided to move out. Death is often synonymous of tremendous ritual expenditures and constitutes as such a utility risk households have to deal with.

The result for girls is not surprising in the Malagasy context and has been observed by other researchers (see e.g. Cogneau et al. 2003). Results do not significantly differ when one substitutes reported shocks in ricefields for transitory change in household income (specification 2).

Turning to the dropout model, the coefficient of transitory income is consistently negative, which implies that higher transitory income reduces the probability of dropping out from schooland, by symmetry, that households facing negative shocks tend to withdraw their children from school. This result suggests that households in rural Madagascar face binding borrowing constraints and divert child time away from education when confronted with negative income shocks. Results also indicate that having younger brothers increases the probability to drop out from school. With the exception of age and rank among siblings, none of the other child-specific variables is found to have discernable effects on school dropout. Here again, substituting reported shock in rice fields for transitory change in household income provides comparable results: the bigger the magnitude of shock in rice fields and the bigger the size of land devoted to rice cultivation, the higher the probability to drop out from school.

6. Conclusion

Consumption-smoothing market mechanisms are quite limited in the Malagasy context. As a result, most rural households - whose incomes can be extremely volatile due to weather conditions, pests, insects, rodents and other calamities - need to rely on nonmarket mechanisms or adopt multi-faceted strategies to cope with risk. In this paper, we have examined whether crop shocks and other types of shocks affect schooling decisions for children. We argue that this would indicate that parents obtain an informal income insurance by letting their children work.

Using five rounds of household panel data from four regions of Madagascar, we investigated whether children's propensity to join school and to drop out of school responds to transient shocks. We also investigated issues such as gender and intrahousehold resource allocation. In order to do so, we first derived an estimate of agricultural income shocks and then regressed schooling decisions (either to enter into school or to dropout of school) on this estimate and other explanatory variables such as child age.

We find that transitory income affects children's school dropout behaviors significantly but not school entrance. This result is consistent with the observation that children's participation to household chores and agricultural activities increases with age. Parents who need to put their children to work will rely on their older rather than younger children. The probability of school entrance appears nevertheless to be sensitive to shocks in the demographic structure of the household since it is negatively correlated with the death or moving out of elderly household members. Our analysis also suggests that parents in our sample favor girls in terms of education. Lastly, we find weak evidence of resource competition among siblings.

The paper can be extended in two directions. First, in order to understand what types of mecanisms could mitigate households reliance on children labor to cope with risk, it would be interesting to investigate whether different types of households respond to shocks differently. Second, the paper would also benefit from a complementary empirical analysis of whether households facing more volatile income stream get lower education outcomes, as found by Kazianga (2005) in Burkina Faso. This is left for further research.

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Table 1 - Dynamic attrition logit model with focus on lagged shocks

Dependent variable is 1if individual attrites in current period, 0 otherwise

Lagged individual characteristics	
Age	0.188 (0.000)***
Age squared	-0.003 (0.008)***
Sex (1: Girl; 0: Boy)	0.169 (0.000)***
Child of head	-0.548 (0.000)***
Rank if child of head	-0.159 (0.000)***
Lagged household characteristics	
Consumption per capita (/1,000,000)	-0.045 (0.658)
Household size	0.093 (0.000)***
Lagged shock variables	
Transitory income	0.382 (0.212)
Number of elderly members who either died or moved out	0.116 (0.263)
Village x Year dummies	Included but not shown
Intercept	-4.338 (0.000)***
Number of observations	21,787

Robust p values in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2 - Frequency of shocks

	Rice fields		Maize fields	
Number of shocks across five survey rounds	Freq.	Percent	Freq.	Percent
0	29	3.1	366	38.9
1	110	11.7	200	21.2
2	213	22.6	171	18.1
3	281	29.8	136	14.4
4	227	24.1	58	6.2
5	82	8.7	11	1.2
Total	942	100	942	100

Table 3a - Magnitude of shocks on rice fields, by year

Observatory	Year	No loss	Moderate losses	Heavy losses	Harvest reduced to nothing
Antalaha	1998	19.6%	56.7%	23.5%	0.2%
	1999	38.8%	47.6%	13.6%	0.0%
	2000	4.0%	27.0%	63.2%	5.7%
	2001	33.3%	48.8%	17.4%	0.6%
	2002	52.9%	20.6%	26.1%	0.3%
Antsirabe	1998	50.6%	32.9%	16.1%	0.3%
	1999	41.3%	35.1%	22.9%	0.7%
	2000	8.4%	24.7%	66.1%	0.8%
	2001	64.8%	15.9%	18.9%	0.5%
	2002	67.3%	12.0%	19.5%	1.2%
Marovoay	1998	58.3%	19.0%	22.6%	0.2%
	1999	28.2%	20.0%	35.4%	16.3%
	2000	44.1%	26.5%	24.4%	5.1%
	2001	54.6%	24.9%	16.9%	3.7%
	2002	53.2%	28.5%	17.7%	0.6%

Note: In Tulear, the fourth observatory, households do not produce rice.

Table 3b - Magnitude of shocks on cassava fields, by year

Observatory	Year	No loss	Moderate losses	Heavy losses	Harvest reduced to nothing
Antalaha	1998	76.0%	15.8%	8.3%	0.0%
	1999	81.9%	12.9%	4.9%	0.4%
	2000	61.5%	13.2%	17.2%	8.0%
	2001	96.9%	2.3%	0.8%	0.0%
	2002	87.8%	7.5%	4.5%	0.2%
Antsirabe	1998	82.3%	9.7%	8.0%	0.0%
	1999	73.4%	11.8%	14.2%	0.7%
	2000	53.9%	21.0%	24.3%	0.8%
	2001	90.7%	2.8%	4.5%	2.0%
	2002	99.0%	0.5%	0.5%	0.0%
Marovoay	1998	97.6%	0.5%	2.0%	0.0%
	1999	94.2%	2.5%	2.5%	0.8%
	2000	95.5%	1.6%	2.5%	0.4%
	2001	97.1%	2.3%	0.4%	0.2%
	2002	97.3%	1.6%	1.2%	0.0%
Tulear	1998	41.8%	32.6%	19.1%	6.5%
	1999	68.8%	16.0%	10.7%	4.5%
	2000	31.2%	10.3%	18.5%	40.0%
	2001	32.8%	13.9%	36.8%	16.5%
	2002	Not surveyed that year			

Table 4 - Probability to drop out from school and shocks

Shocks on rice fields

	Antalaha		Antsirabe		Marovoay		Tulear	
	No loss	Partial or complete loss	No loss	Partial or complete loss	No loss	Partial or complete loss	No loss	Partial or complete loss
1998	4.3%	13.3%	9.0%	11.7%	15.6%	15.7%	-	-
1999	15.0%	9.7%	16.4%	13.7%	12.6%	14.5%	-	-
2000	5.3%	9.5%	13.6%	7.0%	12.4%	15.5%	-	-
2001	8.8%	13.0%	12.3%	12.0%	10.6%	15.4%	-	-
2002	5.9%	8.5%	14.6%	9.9%	12.0%	11.0%	-	-

Shocks on maize fields

	Antalaha		Antsirabe		Marovoay		Tulear	
	No loss	Partial or complete loss	No loss	Partial or complete loss	No loss	Partial or complete loss	No loss	Partial or complete loss
1998	10.8%	21.6%	8.9%	13.0%	15.6%	16.7%	17.6%	17.0%
1999	11.3%	20.0%	15.8%	13.8%	15.0%	5.0%	18.1%	11.9%
2000	8.7%	12.5%	6.3%	7.8%	14.8%	5.0%	16.6%	12.8%
2001	11.4%	18.8%	14.8%	10.3%	13.6%	6.8%	13.6%	13.3%
2002	7.1%	12.5%	12.7%	14.7%	12.0%	3.3%	-	-

Table 5 - Pairwise correlation of schooling rate, per capita income mean and deviation, and rainfall deviation (village level)

	Antalaha	Antsirabe	Marovoay	Tuléar
Mean income per capita	0.095 (0.000)***	0.180 (0.000)***	0.150 (0.000)***	0.073 (0.003)***
Deviation of income per capita from long-term average	0.040 (0.079)*	0.013 (0.523)	0.011 (0.609)	0.076 (0.005)***
Deviation of rainfall from long-term average	0.063 (0.002)***	0.007 (0.705)	0.022 (0.278)	0.065 (0.008)***

p values in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6 - Summary statistics of variables used in income regressions

	Antalaha	Antsirabe	Marovoay	Tulear
Total annual household income	6,003,789 (7,549,550)	3,446,310 (3,217,945)	5,449,929 5,430,779	1,919,666 2,481,261
Physical Assets				
Number of vanilla trees aged 3-	304.5 (781.2)			
Number of vanilla trees aged 3-8	364.8 (942.7)			
Number of vanilla trees aged 8+	123.0 (450.3)			
Land area (acres)	133.7 (117.1)	81.2 (102.4)	130.3 (140.1)	
% of irrigated land	0.27 (0.39)	0.79 (0.34)	0.68 (0.43)	
Number of bullocks	0.53 (1.26)	0.87 (1.34)	0.96 (2.14)	0.65 (1.32)
Number of buffalos	0.26 (0.86)	0.63 (2.92)	1.15 (5.17)	4.51 (11.14)
Number of cows	0.39 (3.67)	0.46 (0.95)	0.57 (2.75)	1.73 (6.16)
Number of pigs	0.20 (0.86)	0.55 (1.21)	0.26 (1.33)	0.01 (0.48)
Human Assets				
Number of children aged 5-	0.96 (0.95)	1.23 (1.08)	0.96 (0.99)	1.47 (1.21)
Number of children aged 5-15	1.56 (1.38)	1.66 (1.41)	1.55 (1.35)	1.76 (1.65)
Number of young adults aged 15-20	0.59 (0.83)	0.70 (0.92)	0.64 (0.88)	0.70 (0.90)
Number of adults aged 20-65	2.00 (0.93)	2.18 (0.96)	2.15 (1.05)	2.04 (1.01)
Number of elders aged 65+	0.17 (0.44)	0.16 (0.46)	0.20 (0.47)	0.12 (0.36)
Shock Variables				
Rainfall deviation	-17.5 (164.8)	-46.7 (169.9)	-61.4 (112.6)	-7.1 (131.1)
Rainfall deviation squared	27.5 (24.1)	31.0 (29.7)	16.4 (23.3)	17.2 (21.0)
Rice field shock	0.85 (0.82)	0.69 (0.85)	0.72 (0.92)	0.00 (0.02)
Rice field shock x area planted in rice	130.3 (201.0)	54.7 (136.4)	119.1 (279.5)	
Maize field shock	0.10 (0.44)	0.66 (0.86)	0.09 (0.39)	1.27 (1.41)
Other field shock	0.74 (0.98)	0.44 (0.80)	0.06 (0.31)	0.83 (1.21)
Tuber. Field shock	0.25 (0.62)	0.26 (0.63)	0.05 (0.30)	0.94 (1.13)
Number of observations	3,261	3,598	3,223	2,320

Table 7 – Fixed effects estimates of the determinants of income

Dependent variable is log(total income)

	Antalaha	Antsirabe	Marovoay	Tulear
Farm characteristics				
Number of vanilla trees aged 3-	0.0000 (3.19)***			
Number of vanilla trees aged 3-8	0.0000 (3.79)***			
Number of vanilla trees aged 8+	0.0001 (3.13)***			
Land area (acres)	0.0010 (6.57)***	0.0011 (7.21)***	0.0016 (11.83)***	
% irrigated	0.0267 (0.83)	0.0319 (1.20)	0.0955 (3.37)***	
Number of children aged 5-	0.0432 (2.32)**	0.0345 (2.34)**	0.0136 (0.89)	-0.0204 (0.53)
Number of children aged 5-15	0.0774 (4.96)***	0.0474 (3.52)***	0.0342 (2.75)***	0.0853 (2.49)**
Number of young adults aged 15-20	0.0918 (4.49)***	0.0573 (3.70)***	0.0885 (5.48)***	0.0403 (0.86)
Number of adults aged 20-65	0.1223 (5.96)***	0.0787 (4.69)***	0.1320 (8.81)***	-0.0525 (1.15)
Number of elders aged 65+	-0.0121 (0.26)	0.0160 (0.31)	0.0524 (1.26)	0.0805 (0.51)
Number of bullocks	0.0409 (3.46)***	0.0584 (5.57)***	0.0127 (2.29)**	0.0815 (3.68)***
Number of buffalos	0.0238 (1.55)	0.0189 (5.46)***	0.0113 (5.33)***	0.0297 (8.98)***
Number of cows	0.0088 (0.58)	0.0828 (7.13)***	0.0224 (6.28)***	0.0181 (3.32)***
Number of pigs	0.0140 (1.03)	0.0350 (4.46)***	0.0026 (0.37)	
Rainfall Variables				
Rainfall deviation from long-term average	0.0014 (11.37)***	0.0002 (3.04)***	-0.0015 (8.89)***	-0.0032 (5.30)***
Rainfall deviation squared[(a)]	0.0222 (23.60)***	0.0013 (2.88)***	-0.0008 (1.09)	0.0245 (5.99)***
Rainfall deviation x Plain area[(a)]	-0.0022 (3.50)***	-0.0008 (0.61)	0.0008 (1.40)	
x Low ground area[(a)]	-0.0029 (1.08)	-0.0002 (0.25)	-0.0017 (0.43)	
x Tavy area[(a)]	0.0064 (0.76)	-0.0304 (2.67)***	0.2074 (1.45)	
x Tanety area[(a)]	-0.0002 (0.15)	0.0094 (3.80)***	-0.0068 (1.62)	
Other Transitory Shock Variables				
Rice field shock x area planted in rice	-0.0005 (5.02)***	0.0001 (0.78)	-0.0003 (6.27)***	
Maize field shock	-0.0300 (1.18)	-0.0086 (0.73)	-0.0757 (3.06)***	-0.0038 (0.14)
Other field shock	-0.0323 (2.32)**	-0.0099 (0.85)	-0.0129 (0.45)	0.0334 (1.15)
Tuber. field shock	0.0141 (0.77)	0.0047 (0.33)	0.0381 (1.23)	0.0094 (0.27)
Year dummies	Included but not shown			
Constant	13.7386 (194.79)***	14.1109 (233.10)***	14.3498 (283.89)***	12.9852 (80.07)***
Number of observations	3,261	3,597	3,223	2,320
Number of households	1,235	847	1,094	996
R-squared	0.37	0.12	0.24	0.17

Table 8 - Summary statistics of variables used in entrant and dropout models

	Entrant model		Dropout model	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Dependent variables				
P(Enter)	0.271	0.444		
P(Drop out)			0.182	0.386
Independent variables				
Sex (1: Girl; 0: Boy)	0.482	0.500	0.489	0.500
Age	6.3	2.1	12.1	3.1
Child of head	0.817	0.387	0.881	0.324
Rank if child of head	3.4	2.8	3.5	2.4
Number of older sisters	1.4	1.2	1.0	1.1
Number of older brothers	0.8	0.9	1.3	1.2
Number of younger sisters	1.5	1.4	1.2	1.1
Number of younger brothers	0.8	0.9	1.4	1.3
Number of elderly members who either died or moved out	0.1	0.3	0.0	0.1
Transitory change in household income	-0.030	0.097	-0.042	0.110
Rice field shock x rice area	98.7	213.7	128.7	238.8
Number of observations	5,789		6,379	
Number of households	996		713	

Table 9 - Conditional logit of entrant model

	(1)	(2)
Characteristics of the child		
Sex (1: Girl; 0: Boy)	0.455 (0.004)***	0.463 (0.003)***
Child of head	1.902 (0.000)***	1.901 (0.000)***
Rank if child of head	-0.130 (0.005)***	-0.128 (0.005)***
Age dummies	Included but not shown	
Number of siblings		
Number of older sisters	-0.010 (0.913)	-0.008 (0.935)
Number of older brothers	0.029 (0.747)	0.019 (0.826)
Number of younger sisters	0.156 (0.127)	0.143 (0.158)
Number of younger brothers	0.086 (0.389)	0.076 (0.446)
Shock variables		
Number of elderly members who either died or moved out	-2.894 (0.000)***	-2.907 (0.000)***
Transitory change in household income	0.278 (0.697)	
Rice field shock x rice area		-0.000 (0.989)
Village x year dummies	Included but not shown	
Number of observations	5,789	5,848
Number of households	996	1005

p values in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 10 - Conditional logit of dropout model

	(1)	(2)
Characteristics of child		
Sex (1: Girl; 0: Boy)	-0.119 (0.405)	-0.110 (0.442)
Child of head	-0.134 (0.599)	-0.127 (0.619)
Rank if child of head	-0.097 (0.021)**	-0.104 (0.013)**
Age dummies	Included but not shown	
Number of siblings		
Number of older sisters	-0.043 (0.621)	-0.036 (0.675)
Number of older brothers	0.084 (0.323)	0.081 (0.340)
Number of younger sisters	0.122 (0.141)	0.123 (0.134)
Number of younger brothers	0.199 (0.013)**	0.195 (0.014)**
Shock variables		
Number of elderly members who either died or moved out	0.588 (0.104)	0.599 (0.096)*
Transitory change in household income	-1.534 (0.007)***	
Rice field shock x rice area		0.000 (0.044)**
Village x year dummies	Included but not shown	
Number of observations	6,379	6,430
Number of households	713	718

p values in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Figure 1 - Probability of school entry by gender

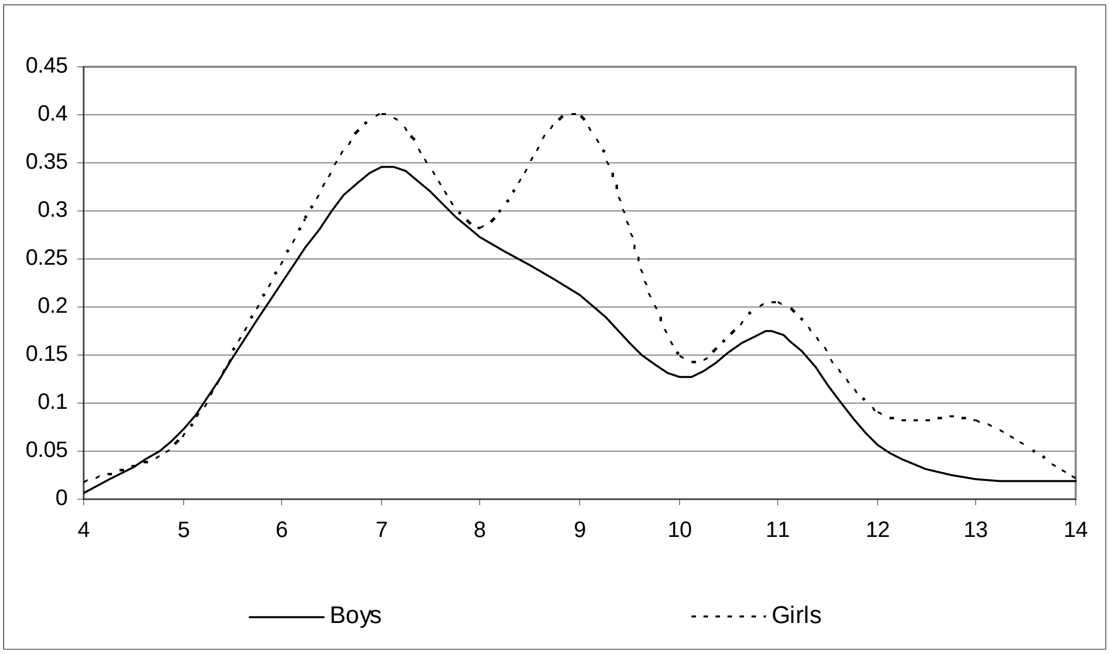

Figure 2 - Probability of school dropout by gender

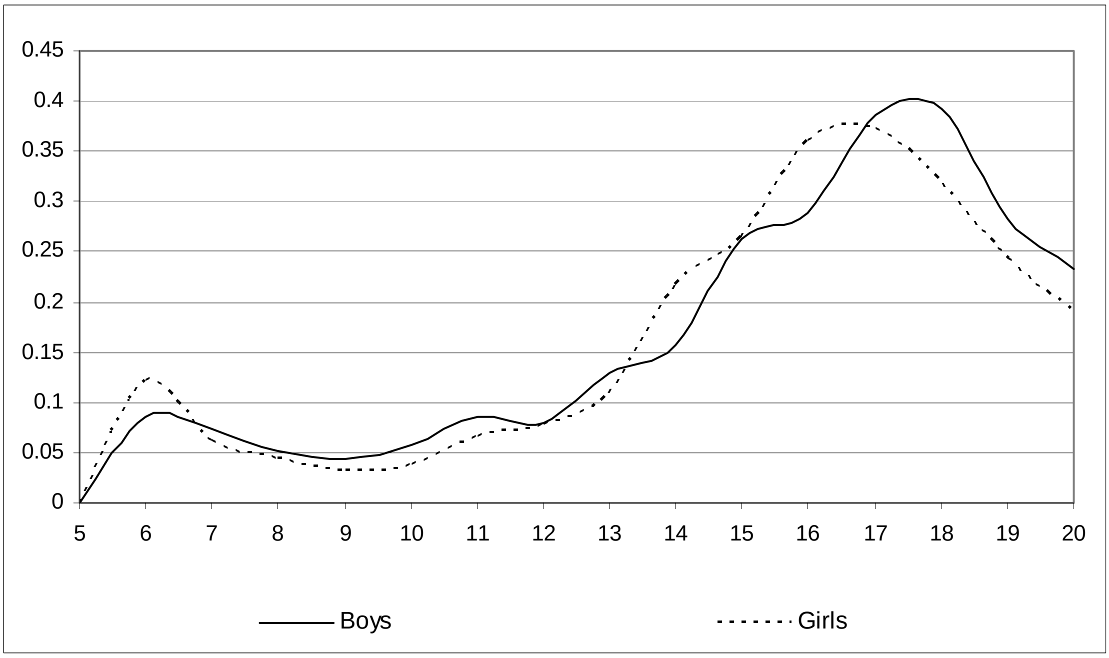

Figure 3 - Percentage of boys and girls involved in household duties or agricultural labor, 2002