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EDUCATION AS A PRECAUTIONARY ASSET

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Education as a Precautionary Asset

Angela Cipollone *

Abstract

By using data from the latest wave of the Indonesia Life Family Survey, this paper investigates whether child time allocation depends on the joint impact of liquidity constraints, risk attitudes and time preferences. We employ a double selection model of school hours to control for endogeneity of borrowing constraints and sample selection in school enrolment. Our measures of time preferences and risk attitudes are elicited from individuals' responses to hypothetical gambles, and households' risk profile is proxied by the past occurrence of shocks. It will be shown that, under liquidity constraints, risk averse parents raise a precautionary demand for education as an ex-ante risk coping strategy in order to insure future consumption through higher returns from children's work.

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1 Introduction

The economic literature investigating the determinants of child labor can be divided in two parallel, though separated, strands: one emphasizing the role of capital market failures; the other emphasizing the importance of subsistence concerns and parental preferences.

This paper proposes an empirical framework to simultaneously account for both, by investigating whether and to which extent children's time allocation depends either on the preclusion of borrowing possibilities, and on risk attitudes and time preferences. We deem that such an analysis provides a relevant contribution to the existing literature which mostly ignore the possibility that time preferences, risk attitudes and borrowing constraints interplay in affecting school investments. On the one hand, the presence of borrowing constraints directly motivates households to supply more child labor as a substitute for the optimal amount of borrowing. On the other hand, the preclusion of borrowing possibilities may indirectly affect school investments by influencing the likely impact of other characteristics. For example, it can be reasonably thought that the impact of risk aversion on school investments is more relevant among liquidity constrained households.

This paper employs a double selection model of school hours to control for endogeneity of borrowing constraints and sample selection in school enrolment, and adds time preferences, risk attitudes and proxies for risks and shocks among the relevant regressors. To this aim, we exploit measures of time preferences and risk attitudes elicited from individuals' responses to hypothetical gambles and consider the past occurrence of shocks to proxy households' risk profiles.

It will be shown that, under liquidity constraints, risk averse parents raise a precautionary demand for education as an ex-ante risk coping strategy in order to insure future consumption through higher returns from children's work.

The paper is structured as follows. Section 2 presents a brief review of the relevant literature. In section 3, we develop a simple theoretical model on the likely impact of parents' risk and time preferences and liquidity constraints on children's time allocation. Section 4 presents the dataset and, specifically, how the key variables for risk and time preferences and exogenous income shocks are constructed. Section 5 outlines the hypotheses to be empirically tested. Section 6 discusses the empirical strategy used in the proceeding of the paper to verify our model's predictions while section 7 presents the main results. Section 8 concludes.

2 Related literature

The analyses of the determinants of child time-use have typically focused on the role of capital market failures, subsistence concerns and parental preferences.

2.1 The role of capital market failures

The literature emphasizing the role of capital market failures on child labor and early education is extensive, both theoretically and empirically.

Baland and Robinson (2000) show that child labor is inefficient when the family is so poor that the parents do not leave bequests to their children. By adopting a two-periods model, they show that, despite parental altruism, child labor is inefficient when it is used by parents as a substitute for negative bequests (to transfer income from children to parents), or as a substitute for borrowing (to transfer income from the future to the present). Pouliot (2006) introduces uncertainty to the Baland and Robinson's model of child labor. He finds that, under non-borrowing restrictions, the set of conditions generating an inefficiently high level of child labor is determined by the presence of uncertain returns to human capital and incompleteness of insurance markets. Rajan (2001) adopts a two-periods model to study the relationship between income inequality and the incidence of child labor in presence of credit constraints. The model shows that, when individuals have different abilities, higher income inequality is associated with higher incidence of child labor. For each level of ability there is a threshold level of parental income such that households below that threshold send their children to work. Parsons and Goldin (1989) show that the sub-optimality of schooling investments is closely-related to the availability of efficient capital markets. The negative impact of credit constraints on investments in early education has been discussed also by Laitner (1997), Parsons and Goldin (1989), and Jacoby and Skoufias (1997).

There is an abundance of empirical evidence concerning the role of incomplete financial markets on educational attainment, in response to shocks. Some of these recent findings are provided – among the others – by Guarcello, Mealli e Rosati (2010), Fitzsimons (2007), Beegle, Dehejia and Gatti (2005), Dehejia and Gatti (2002), Edmonds (2002), Pörtner (2001), Ranjan (2001), Jacoby and Skoufias (1997), Jacoby (1994).

2.2 The role of risk attitudes and time preferences

Given the uncertainty surrounding the income stream, it is not surprising that risk attitudes and time preferences have played a key role in the theory of human capital accumulation. In practice, however, given the difficult job of measuring risk and time preferences, their impact on educational investments has attracted limited attention in the empirical literature and with ambiguous results.

In some empirical models of human capital accumulation, a parameter of constant risk aversion has been included; however, such an approach does not allow variation in risk preferences across individuals to play a role in the investment decision-making process. Belzil and Hansen (2004), for example, estimate a dynamic programming model of schooling decisions where the degree of risk aversion is inferred from school decisions. In this model, individuals are assumed to be heterogeneous with respect to ability yet homogenous with respect to the degree of risk aversion.

An important exception in the literature is Shaw (1996) who jointly models investments in risky human capital and financial wealth allowing for interpersonal differences in risk preferences.

Among the others, these papers typically treat human capital accumulation as a standard investment process, predicting that the less risk averse individuals invest in relatively high levels of education.

Differently from the previous works, Belzil and Hansen (2004) find that a counterfactual increase in risk aversion induces a precautionary accumulation of human capital. Gould, Moav, Weinberg (2001) find similar results. They analyze the impact of human capital depreciation risks on the choice of the type of education, asserting that in periods of technological progress, risk aversion induces workers to invest in general education to avoid the risk of losing their technology-specific skills. Their findings however do not control for any possible variation in this response due to capital markets conditions and to the source of expected risks.

2.3 A new perspective: linking the two approaches

While the role of risk attitudes, time preferences and capital market failures on school investments has been widely investigated especially in the theoretical literature, at our knowledge there is still no attempt to analyze their joint effect.

This paper aims to fit this gap by exploring whether the lack of insurance and capital markets exerts heterogeneous effects on school investments, according to risks attitudes and time preferences. It is commonly thought that uninsured exposure to income risks induce parents to rely on internal assets (such as income from child labor) to secure a smoothed consumption path. This paper is intended to verify whether this occurs independently on risk attitudes and time preferences. Indeed, in case of preference for precautionary wealth accumulation (elicited by a positive third derivative of the utility function), parents with an uninsured exposure to income risks (due to the preclusion of borrowing and private insurance, for example) may desire to raise a precautionary demand for education in order to safeguard future consumption through higher returns from their children's work. Instead, parents with access to capital markets can rely on borrowing or private insurance.

3 The model

Our model is comprised of two periods, referred to 1 and 2. At the beginning of period 1, parents decide how to allocate their children's unit time endowment between child labor l_c and human capital accumulation $1 - l_c$, where l_c represents the fraction of a child's unit time endowment allocated to work.[1] For simplicity, we assume that parents earn income A, in periods 1 and 2. We introduce uncertainty, by allowing parental income to include an absolutely continuous negative random variable Φ, with $E(\Phi) = 0$ and $var(\Phi) = \sigma^2_\Phi$.

In period 2, each child supplies $h(1 - l_c)$ units of labor, where $h(\cdot)$ represents a human capital production function of the following form:[2]

$$h(1 - l_c) = \theta (1 - l_c)^\alpha \kappa^\beta. \tag{1}$$

where: $\alpha, \beta > 0$; $\alpha + \beta < 1$; $(1 - l_c)$ is the time spent at school, κ represents a given amount of goods invested in human capital, θ is a productivity parameter (i.e., learning ability). We normalize the returns to human capital to 1. Parents' utility function is separable in period 1 and period 2 consumption (c_p^1 and c_p^2, respectively) and is denoted by:

$$W_p\left(c_p^1, c_p^2\right) = U\left(c_p^1\right) + \frac{1+r}{1+\delta} EU\left(c_p^2\right) \tag{2}$$

[1] In the literature there is a tendency to narrow the discussion and analysis of the determinants of children's activities to two non-leisure activities— market labor and schooling. There are a number of reasons why there has been a focus in the empirical literature on children market labor and schooling. First, both are important outcome variables that policymakers like to target. Second, it embeds the evidence that not only work "outside" home (i.e that for wage) should to be considered as "child labor". In developing countries the time children do not spend at school is largely dedicated to work at home or in the family enterprise which can be as hard as work outside.

[2] See, Trostel (2004), Ben-Porath (1967).

where $U(\cdot)$ is twice continuously differentiable and strictly concave, r is the constant net return to financial asset and δ is the discount factor with $\frac{1+r}{1+\delta} < 1$.[3]

The interest in investigating the role of risk preferences on child time allocation motivates the adoption of an isoelastic utility function: $u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$, with γ as absolute coefficient of risk aversion and absolute coefficient of prudence. Parents can transfer income between periods by saving (denoted $b < 0$) or borrowing (denoted $b > 0$). Capital markets are imperfect and some parents are prevented from borrowing. Borrowing restrictions are exogenously determined. The household maximization problem can be represented as,

$$\max_{b,l_c} U\left(c_p^1\right) + \frac{1+r}{1+\delta} EU\left(c_p^2\right) \tag{3}$$

subject to:

$$\begin{aligned} c_p^1 &= A + l_c + b && (4) \\ c_p^2 &= A + h(1-l_c) - b + \Phi && (5) \end{aligned}$$

The following first order conditions can be derived,

$$\begin{aligned} U'(A + l_c + b) &= \frac{1+r}{1+\delta} EU'(A + h(1-l_c) - b + \Phi), \; b = b^* < 0 && (6) \\ U'(A + l_c) &> \frac{1+r}{1+\delta} EU'(A + h(1-l_c) + \Phi), \; b = 0 && (7) \\ U'(A + l_c + b) &= \frac{1+r}{1+\delta} EU'(A + h(1-l_c) - b + \Phi)\, h'(1-l_c) && (8) \end{aligned}$$

b^* can be interpreted as the optimal amount of parental borrowing. If parents do not desire to borrow ($b^* \leq 0$), then consumption always equals its optimal level; otherwise ($b^* > 0$), consumption may be inefficiently low if borrowing is prevented. In this case households are considered as liquidity constrained. Using the first order conditions, the following conclusions can be established.

Proposition 1 *If borrowing is interior, then the laissez-faire level of child labor is efficient,* $h'(1-l_c) = 1$*. Hence, in absence of liquidity constraints, the allocation of children's time does not depend either on goods and productivity parameters of the human capital production function or on expected income risks, even in presence of a possibly high coefficient of relative risk aversion* $\gamma > 0$*.*

Proposition 2 *If borrowing is at corner, then* $h'(1-l_c) > 1$*, and the laissez-level of child labor is inefficiently high. When capital markets are imperfect and parents cannot borrow, child labor supply is used to smooth the expected marginal utilities from consumption between period 1 and period 2. As a consequence, the marginal investment in schooling may be inefficiently low.*

[3] As in Carroll (2001), we assume that consumers are impatient, in the sense that if there were no uncertainty or liquidity constraints, they would choose to spend more than current income. For many people, particularly those close to subsistence in low developed countries, this assumption seems to be a natural one.

By plugging the exact functional forms for the utility and the human capital production functions, equation 8 with $b = 0$ becomes:

$$\frac{1+r}{1+\delta} E\left(\frac{A + h\left(1 - l_c\right) + \Phi}{A + l_c}\right)^{-\gamma} = \theta\alpha\left(1 - l_c\right)^{\alpha-1}\kappa^{\beta} \tag{9}$$

We take logs in equation 9 and use the following hypotheses on the consumption growth distribution

$$\begin{aligned}
\ln c_p^2 - \ln c_p^1 &= \Delta\ln c_p^2 | I_1 \sim N\left(\mu, \sigma_\Phi^2\right) && (10)\\
\Delta\ln c_p^2 - \mu &= \Delta\ln c_p^2 - E\Delta\ln c_p^2 = \Phi && (11)\\
\mu &= \theta\left(1 - l_c\right)^{\alpha}\kappa^{\beta} - l_c && (12)
\end{aligned}$$

where first and second moments are conditioned to the set of information available at time 1, to get:[4]

$$\ln\alpha\theta\kappa^{\beta} + \underbrace{\left(\alpha - 1\right)\ln\left(1 - l_c\right)}_{>0} = \ln\frac{1+r}{1+\delta} - \gamma\mu + \frac{1}{2}\gamma^2\sigma_\Phi^2 \tag{13}$$

The first two terms on the right-hand side of equation 13 represent the determinist component of the marginal return to human capital investments, which decreases with the number of hours spent at school and with the coefficient of absolute risk aversion $A\left(c_p^1\right) = \gamma$. The last term on the right-hand side measures the volatile component of the marginal return to human capital investments, which increases with the expected variability of future income $\left(\sigma_\Phi^2\right)$ and with the squared of the coefficient of absolute risk aversion $\left(A\left(c_p^1\right)\right)^2 = \gamma^2$. According to 13, in presence of liquidity constraints, the allocation of children's time depends on expected income risks, on the degree of time preference ($\delta > 0$) and on the coefficient of absolute risk aversion.

Rearranging 13, we get:

$$\left(\alpha - 1\right)\ln\left(1 - l_c\right) + \gamma\left(\theta\left(1 - l_c\right)^{\alpha}\kappa^{\beta} - l_c\right) = \ln\frac{1+r}{1+\delta} + \frac{1}{2}\gamma^2\sigma_\Phi^2 - \ln\alpha\theta\kappa^{\beta} \tag{14}$$

Being $\alpha, \beta, \kappa, \theta$ invariant, it is straightforward to notice that any increase in the right-hand side of 14 implies a correspondent increase in the left-hand side of the same equation, which occurs at larger investments in early education (an increase in $(1 - l_c)$). Hence, any increase of expected income risks implies an upward shift in the number of hours children spend at school. Moreover, at any increase of σ_Φ^2, the likely impact on educational investments is larger at increasing coefficient of absolute risk aversion. Indeed, if households were not risk averse ($\gamma = 0$), the time allocation response to σ_Φ^2 would be null; instead, a positive value of γ requires a positive number of hours at school to restore the equilibrium. In other words, under liquidity constraints, risk averse households are characterized by a precautionary demand for education: education is thought a precautionary asset, an insurance device against expected income risks. In a similar vein, it can be noticed that household's impatience (defined

[4] If a random variable X is distributed with a lognormal probability distribution function, then: $\ln E\left(X\right) = E\ln(X) + \frac{1}{2}var\left(\ln\left(X\right)\right)$.

by δ) lowers the number of hours children spend at school. This result suggests that households with a higher inter-temporal preference are more inclined to withdraw their children from schooling and to send them at work in order to feed up current consumption. Finally, it is easy to notice that the time allocation response to expected income risks and parental preferences is lower at increasing child's ability, α.

Hence, in presence of liquidity constraints, household's characteristics (such as risk attitudes, time preferences and subjective expectations of income risks) interact in shaping the optimal allocation of child time. Conversely, in absence of liquidity constraints, the allocation of children's time is not affected by interactions between risk preferences and expected income risks. As a consequence, we can conclude that two human capital production functions exists: one for liquidity constrained households and another for non-constrained households.

4 Data

We use data from the Indonesia Life Family Survey to verify our model's predictions. The IFLS data have been largely used in the literature to study the likely effect of risks on child labor supply. This paper adds to and updates this literature by considering the most recent wave of the survey (the IFLS 4), fielded in 2007/2008.

The Indonesian Family Life Survey (IFLS) is an on-going longitudinal survey in Indonesia, containing widespread current and retrospective information about adults, children and household's assets. The sample is representative of about 83% of the Indonesian population and contains over 30,000 individuals living in 13 of the 27 provinces in the country. The choice to use this dataset has been motivated by the extensive set of information provided. Indeed, the IFLS contains a wealth of information collected at the individual and household level, including multiple indicators of economic well-being (consumption, income, and assets); education, migration, and labor market outcomes; marriage, fertility, and contraceptive use; health status, use of health care, and health insurance;relationships among coresident and non-coresident family members; processes underlying household decision-making; transfers among family members and inter-generational mobility; and participation in community activities. Compared to the previous rounds of the survey, IFLS4 provides a new set of information on risk preferences and discount rate. In particular, and as it will be discussed below, the discount rate will be measured from hypothetical questions on whether the respondent prefers a lower amount of money now or a higher amount in one year. Risk preference coefficients will be extrapolated from hypothetical questions of a choice between a job that guarantees a certain amount of lifetime income, and another job that gives the individual a 50-50 chance of getting a higher or lower amount than the previous one. Finally, since the waves of the IFLS span the period from several years before the economic crisis hit Indonesia to one year prior to the crisis as well as three years after the incident, extensive research can be carried out regarding the living conditions and coping mechanisms of Indonesian households during this tumultuous time period.

Figure 1 presents definitions and summary statistics of the variables used in the analysis. The dependent variable is the number of school hours during the last week or the last week the school was in session during the school year of the survey, 2007-2008, for any child between 6 and 17 years old (SCHHOURS). This variable does not take into account past temporary interruptions to schooling, which are one way of dealing with contemporaneous shocks. Hence, it is plausible to assume that any income shock occurred until 2006 should not directly affect the number of hours children currently spend at school but rather to indirectly bear on it, by affecting the expectations of future earnings volatility as discussed below.

[Table 1 around here]

4.1 Measuring income risks

This paper uses past occurrence of shocks and the cross-sectional coefficient of variation of households income to proxy the risk profiles of the households.[5] This approach is based on the assumption that households use past income volatility to predict future volatility, which we believe is a reasonable starting point. Ideally, we should measure the uninsured portion of the unanticipated components of income variability to obtain an accurate representation of the household's exposure to risk. However, the last wave of IFLS does not contain accurate retrospective income information.

To proxy the riskiness profile of income due to past macroeconomic shocks we employed the count variable MRISK. It runs from 0 to 2 which stand for the number of the following shocks the household faced between 2000 and 2006: flood, landslide, volcanic eruption, earthquake, tsunami, windstorm, forest fire, fire, civil strife.

We also include a measure of idiosyncratic risks in parents' job prospects, JRISK. It is a count variable from 0 to 7, standing for the number of years the household's head experienced job termination (in the form of unemployment or inactivity) between 2000 and 2006. JRISK synthesizes the household's head past difficulties to maintain a job, and its inclusion among the independent regressors of school hours estimates quantifies the likely impact of idiosyncratic riskiness in job prospect on educational investments.

Following Guiso et al. (1996), we consider a further measure of income risks, such as the cross-sectional coefficient of variation of households income (HINCM) as proxy for the degree of overall income uncertainty.

4.2 Measuring income shocks

Similarly to uncertainty, we included two indicators for the occurrence of contemporaneous income shocks: MSHOCK and JSHOCK. MSHOCK is a proxy for recent macroeconomic income shocks. It is a count variable from 0 to 3, standing for the number of the following shocks the household has experienced since 2007: flood, landslide, volcanic eruption, earthquake, tsunami, windstorm, forest fire, fire, civil strife. Similarly, JSHOCK is a count variable from 0 to 2, representing the number of years the household's head experienced job termination (in the form of unemployment or inactivity) since 2007. It is as a measure of recent idiosyncratic job shocks experienced by the household's head and quantifies the troubles in maintaining a job.

It might be objected that the school hours response to JRISK and MRISK may be the result of an ex-post risk coping strategy to past persistent job termination events. Indeed, JRISK exhibits a relevant degree of path dependence.[6] Exactly due to this persistence, the variable JSHOCK embeds past persistent income shocks in household's head labor income households have not yet completely

[5] See, among the others, Fitzsimons (2007) and Guiso et al. (1996).

[6] On average, across the whole period 2000-2008, the probability of the household's head to not be employed in t, after having experienced a job termination in is over 50%.

recovered from. Hence, any significant impact of JRISK on school hours is likely to measure the school hours response to any residual information embedded in JRISK which does not concern the current activity status of the household's head. Therefore, the contemporaneous introduction of both JRISK and JSHOCK among the independent regressors of school hours equation contributes to disentangle the impact of JRISK - as a proxy of the riskiness of job prospects (out of any recent shock) - from that of JSHOCK as a proxy of contemporaneous or past persistent shocks in labor income.

With respect to MRISK, 98% and 96% of households who faced shocks on agricultural activities between 2000 and 2006 reported no loss in business and non-business assets, respectively, as a consequence of those events. Similarly, only 23% of households who faced macro shocks between 2000 and 2006 declared its own house was heavily damaged by the disaster; and 89% of those households whose house was slightly or heavily damaged declared to have already rebuilt the house at the time of the survey. Hence, it is plausible to assume that the degree of shock persistence in the case of macro disaster is not significant and, in turn, MRISK represents itself a good proxy for the expected risk profile of households. Alongside MSHOCK, we introduce a further measure of income shocks caused by macroeconomic events, such as CROPLOSS. It is a dummy variable taking value 1 if the household reported at least one event of crop loss in the past 12 months, and 0 otherwise.

4.3 Measuring time preference and risk aversion

To measure parents' degree of risk aversion, a categorical variable RISKPREF has been created. It takes value 1 if the household head is not risk averse, value 2 if the household head is moderately risk averse (MRISKAV), and value 3 if the household head is highly risk averse (HRISKAV). Household's heads are considered as highly (moderately) risk averse if they declare to be more willing to accept a certain amount of rupias (which is lower in the case of moderately risk aversion) compared to playing a lottery in which there is a 50-50 probability to win significantly more or significantly less than the certain amount. In particular, on the bases of the hypothetical lotteries shown in Table 2, the household's head is considered as highly risk averse if he/she answered 1 to at least one of the following questions: SI03, SI04, SI05, SI13, SI14, SI15. The household's head is considered as moderately risk averse if he/she answered 2 to at least one of the following questions: SI13, SI14, SI15; and 1 to at least one of the following questions: SI03, SI04, S015.

Parents' time preferences are captured by the dummy variable HHIMPATIENCE, taking value 1 if the household's head declares to be more focused on the well-being in the presence and the immediate future, and 0 otherwise. In particular, each household is classified as time impatient if the household's head is more willing to accept a 1 million of rupias today, rather than waiting 1 year to get an amount which is significantly higher. On the bases of the hypothetical lotteries shown in Table 2, the household's head is considered as time impatient if he/she answered 1 to at least one of the following hypothetical lotteries: SI21B, SI21C, SI21D.

[Table 2 around here]

4.4 Measuring liquidity constraints

A household is defined as liquidity constrained (LIQCON) if at least one of the following conditions applies: i) the household's head and/or his/her spouse tried to borrow money from non-family members or friends over the past 12 months but the number of reported loans is null, ii) if the household head and/or his/her spouse turned down in his/her efforts to secure a loan from non-family members or friends during the past 12 months, iii) if the household head and/or his/her spouse was not successful in securing a loan from non-family members or friends in the past 12 months, iv) nobody in the household declares to know a place where borrowing money from non-family members or friends.

By adopting this approach, 12.1% of all the children between 6 and 17 years old are found to belong to liquidity constrained households in 2007.

5 Theoretical hypotheses testing

Using the dataset discussed above, the model results outlined in paragraph 3 will be tested along the following lines.

[Hp.1]. The result of proposition 2, according to which the presence of liquidity constraints decreases the time children spend at school, will be tested through the significance of a two-sample mean comparison test of the variable SCHHOURS between liquidity constrained and non-constrained households.

[Hp.2]. Interactions between the proxy variables for expected income risks (JRISK, MRISK, HINCM) and the variables for risk attitudes discussed above (RISKPREF: MRISKAV, HRISKAV) may be used to verify whether, among liquidity constrained households, the presence of exogenous income risks positively affects the number of hours children spend at school at increasing positive degree of parents' risk aversion. For example, the significance of the of the interactions between RISKPREF and MRISK on the amount of time children spend at school will test whether there is a precautionary demand for education due to income risks from macroeconomic shocks. Similarly, interactions between the variables RISKPREF and JRISK will test whether there is a precautionary demand for education due to idiosyncratic risks in parents' job prospects. Finally, interactions between HINCM and RISKPREF will test whether households' perception of overall income uncertainty positively affects child schooling at increasing parents' risk aversion. If households are not liquidity constrained, these interactions should not significantly affect the outcome variable SCHHOURS since, according to our theoretical findings, child labor is not used as an ex-ante risk coping strategy.

[Hp.3]. A negative and significant impact of HHIMPATIENCE on school hours will verify the "Result 4", according to which, in presence of liquidity constraints, a positive degree of impatience exerts a downgrading effect on school hours.

[Hp.4]. To control for the possibility that the likely response of child labor to risks depends positively on the degree of household's wealth, we include three further interactions terms between the percentiles of the wealth index (WEALTHPC), risk attitudes and risk measures. WEALTHPC is the constructed index of household wealth[7] in three quintile categories. The relevance of their coefficients on the school hours regression estimates allows us to investigate whether the response of school hours to the interactions between uncertainty and risk attitudes are sensible to marginal changes in household's wealth (i.e. whether the evidence of a precautionary motive for education is prevalent among wealthier households).

[7] Our wealth index is a composite measure of the cumulative living standard of a household, calculated using easy-to-collect data on a household's ownership of selected assets, such as televisions and bicycles, materials used for housing construction, and types of water access, sanitation facilities, jewelry and savings. Generated with a statistical procedure known as principal components analysis, the Wealth Index places individual households on a continuous scale of relative wealth.

[Hp.5]. Finally, we also included interactions between the three measures of recent idiosyncratic and macroeconomic income shocks (JSHOCK, MSHOCK, CROPLOSS) and RISKPREF on the regression equation of school hours. Any significant difference between the coefficients of the interaction variables JSHOCK×RISKPREF (or MSHOCK×RISKPREF) and those of the interaction variables JRISK×RISKPREF (or MRISK×RISKPREF) might help to understand whether household's responses in terms of educational investments differ according to the timing of shock occurrence. In this paper, we argue that, for liquidity constrained households, expected income risks give rise to a precautionary demand for education (positive signs for the interaction variables JRISK×RISKPREF or MRISK×RISKPREF on school hours regressions). Conversely, the contemporaneous occurrence of adverse income shocks negatively affect the amount of hours children spend at school, with child labor acting as an initial buffer against those shocks (negative signs for the interaction variables JSHOCK×RISKPREF, MSHOCK×RISKPREF or CROPLOSS×RISKPREF on school hours regressions). Again, if households are not liquidity constrained, these interactions should not significantly affect the outcome variable SCHHOURS since, according to our theoretical findings, child labor is not used as a risk coping strategy.

6 The Empirical Strategy

This section discusses the empirical strategy used in the proceeding of the paper to verify the hypotheses listed in the previous paragraph.

Researchers are usually left to compare investments in early education among liquidity constrained households and non-liquidity constrained households. However, the problem of endogeneity (Hausman 1978) of liquidity constraints arises due to the fact that households who invest less in education are more likely to be those who face credit constraints. Because the overall circumstances responsible for differing initial conditions of constrained and unconstrained households are known only to the household and not to the researcher, these cannot be directly controlled to single out the pure effect of liquidity constraints on schooling. For instance, if ability is at least partly inheritable, less able children are more likely to belong to liquidity constrained households and, ceteris paribus, to invest less in education. Then, failure to control for this correlation will yield an estimated liquidity constraints effect on schooling that is biased down. In addition, a problem of sample selection also arises due to the fact that the dependent variable (the number of weekly hours at school) is observed only for a restricted non-random sample. For example, we observe the time at school of a child living in a liquidity constrained household only if the household the child belongs to is liquidity constrained and the child is enrolled in school. Conversely, one observes the time at school of a child living in a non-liquidity constrained household only if the household the child belongs to is not liquidity constrained and the child is enrolled in school. If the samples of liquidity constrained households and of children at school were random draws from the population, a tobit regression of school hours could be fitted, by including credit status as a right-hand-side variable and pooling the entire sample. However, this approach becomes problematic if children in liquidity constrained and non-constrained households differ systematically in the expected amount of school hours not only because of a merely intercept effect but also because of a slope effect. This occurs for example when the returns to different observable attributes vary by credit regime or if the subsample of students is non-randomly selected.[8]

[8] This is indeed the case in many developing and under-developed countries where school enrolment rates are tipically lower.

In other words, estimating a tobit model where non-students are simply treated as zeros may be problematic, as it assumes that the decision to be enrolled in school is qualitatively the same as the decision related to the degree of enrolment in terms of the amount of time spent at school. However, there may be important differences related to these decisions. Consider for example the effect of age: the older the child is, the more likely it is that she is involved in some form of market or non-market work, thereby subtracting time to school. Secondly, children at school may differ from children not at school with respect to unobserved characteristics, such as ability. Hence, treating the decision to abstain from school as a corner solution may provide biased results due to a possible correlation of the error terms. As a consequence, studying the determinants of the amount of children's time at school needs to account for the presence of children who are not enrolled in school at all and to correct for the possible sample selection.

A common means of "correcting" for both the endogeneity and sample selection biases associated with systematic differences between groups is to impose a specific probability distribution structure on the model which explicitly incorporates the selection rule(s). That is the modeling strategy adopted here. We follow Barham and Boucher (1998) in extending the specification of Heckman (1976, 1979) to include two selection criteria before running the school hours regression equations: a rule for credit regime affiliation (first-stage probit) and a rule for the school enrolment decision (second-stage probit).

To account for the possible presence of sample selection biases discussed above, we choose to split up the whole sample into two subsamples: one including children living in liquidity constrained households (denoted by C) and the other including children living in non-liquidity constrained households (denoted by U).

To proceed we estimate the probit for credit regime affiliation first for the whole sample and then generate the Inverse Mill's Ratio (IMR) term for each sub-sample (IMRU1, IMRC1). These terms will then be included in the probit equation explaining enrolment status for each subsample. The appropriate IMR terms from these equations (IMRU2, IMRC2) will then be included in the two final schooling hours equations (one for each subsample, Amemiya 1985).

6.1 Identification issues

As in any model, one must be aware from where identification arises.

The identification approach adopted in this paper relies on Heckman's procedure and sample splitting. From the credit selection equation on the whole sample, the appropriate IMR terms are generated for each credit regime. Then, we opted for splitting up the sample into children living in liquidity constrained households and children living in households with access to capital markets. The IMR terms obtained in the first probit will be included in a second probit equation explaining the school enrolment status for each subsample. The appropriate IMR terms from these equations will then be included in the final SCHHOURS equation of each credit regime.

Identification in the second-stage probit is provided by the presence of an exclusion restriction, the variable GIVASSIST in the credit regime selection rule and by the nonlinearity of the IMR term obtained in the first-stage probit (Heckman, 1978; Wilde, 2000). GIVASSIST and RECASSIST are count variables representing, respectively, the number of times the household has provided or received help in the form of money, goods, services to persons outside the household (other than biological parents, siblings, children) or to other parties (for example like a foundation/organization, friends, and relatives) during the last 12 months (except gifts, souvenirs, etc.). The use of the variable GIVASSIST as an exclusion restriction is based on the assumption that parents care more about their children's wellbeing than about the wellbeing of friends or relatives outside the household. Hence, the amount of assistance received (RECASSIST) is supposed to be positively correlated with school enrolment as it represents a sets of goods and services households members do not longer need to get from child work. Instead, the amount of assistance provided to friends or other relatives (GIVASSIST) is supposed not to affect school enrolment, as parents are typically assign priorities to their children's wellbeing. Conversely, both of them should be significantly correlated with the likelihood for households to be liquidity constrained, since, ceteris paribus, it is reasonable to suppose that better off households are more likely to provide and less likely to receive assistance.

To assess the validity of this identification strategy, we ran an instrumental variable probit of the probability to be enrolled at school including LIQCONS among the relevant regressors and GIVASSIST as instrument for LIQCONS. The Wald test signals a non-rejection of the null hypothesis of exogeneity of LIQCONS in the school enrolment probit. Hence, in principle, the equation of school enrolment would be identified also in absence of any exclusion restriction. Similarly, we performed an instrumental variable regression of SCHHOURS including LIQCONS among the relevant regressors and GIVASSIST as instrument for LIQCONS. The underidentification and weak identification tests conclude in favor of the hypothesis that the model is identified and the excluded instruments are relevant.

Because the IMR terms are nonlinear functions of the variables included in the probit models, then the SCHHOURS regression equations are identified because of this nonlinearity. Since the nonlinearity of the IMR terms arises from the assumption of normality in the probit models, we tested this normality assumption in the school enrolment selection equation for each credit regime. Lagrange multiplier tests conclude that the normality of residuals cannot be rejected for both credit regimes.

The analysis of the inter-quartile ranges of residuals helps us to evaluate whether our double selection model is fairly specified. The inter-quartile range assumes the symmetry of the distribution. Severe outliers consist of those points that are either 3 inter-quartile-ranges below the first quartile or 3 inter-quartile-ranges above the third quartile. The presence of any severe outliers should be sufficient evidence to reject normality at a 5% significance level, while mild outliers are common in samples of any size. In our estimates of school hours, we don't have any severe outliers and the distributions seem fairly symmetric. The residuals have an approximately normal distribution, thereby suggesting that our school hours estimates are well specified.

All details are available from the authors under request.

7 Estimation Results

Our variable of interest is SCHHOURS, standing for the number of school hours during the last week or the last week the school was in session during the school year of the survey, 2007-2008, for any child between 6 and 17 years old.

Sample statistics indicate that this variable differs in mean and variance between liquidity constrained and non-constrained households. The mean value of SCHHOURS is 17.8 for the sample of children living within non-liquidity constrained households and drops to 16.6 for the sample of children living within liquidity constrained households. The correspondent standard deviations are 12.3 and 12.2, respectively. The t-test for sub-samples with unequal variances shows that the mean of SCHHOURS significantly differs between the two groups. The null hypothesis of equality between the two sample means is rejected at a 1% significance level against both the alternative hypotheses. The same results are obtained from the Hotelling's T2 test.

These findings suggest that school hours are significantly related to the credit regime, thereby confirming *[Hp.1]*.

Results from the double selection models (outlined in section 6) complete the overall understanding of the effects of liquidity constraints on school investments.

7.1 Selection equations

The maximum likelihood estimation of the probability of children to live within liquidity constrained households and to be enrolled at school are presented in 3.[9]

[Table 3 around here]

With respect to the credit regime selection equation, goodness of fit measures indicate that the estimated model fits the data reasonably well. The Wald tests showed that the parameter estimates were significantly different from zero. The model correctly predicts the overall probability of households to fall into the true credit regime for 88% of the sample. The results show that the coefficients of most of the variables hypothesized to influence the likelihood for children to belong to liquidity constrained households have the expected signs.

Among the traditional human capital and employment characteristics of the household's head and his/her spouse, a high educational attainment (measured by a level of qualification above upper secondary education) seems to significantly lower the probability for children to live in liquidity constrained households (by between -4.3% and -9.2%). Among household demographic characteristics, larger numbers of household members and of children positively effect the outcome. Ceteris paribus, the probability for children to belong to liquidity constrained households is significantly larger in rural areas (+3.8%). Alongside education, household wealth seems the most relevant determinant for the credit regime affiliation. In particular, at increasing household wealth (measured by the quintiles of household wealth index) the probability for children to belong to liquidity constrained households decreases. The activity status of the household's head also matters: when she is employed in a dependent job, the probability of positive liquidity constraints significantly drops. The variable chosen as exclusion restriction, GIVASSIST, is significantly and inversely related to the likelihood for children to live in households with liquidity constraints.

The models correctly predicts the overall probability of children to be enrolled at school for more than 90% of both samples and the coefficients of most of the explanatory variables have the expected signs and are substantially similar across credit regimes. Ceteris paribus, the probability for children between 6 and 17 years old to go to school lowers with age (-2.9% for the constrained sample and -1.8% for the non-constrained sample) and increases with the educational attainment of the household's head. There is a strong evidence of persistence in child's time use: being at school during the previous school year significantly increases the likelihood to be still enrolled in school by 61% for the sample of children living in liquidity constrained households, and by 52% for the sample of children not living in liquidity constrained households. The degree of persistence in child's time use also matters: any

[9] Additional control variables: number of employed adults in the household, education of the spouse of the household's head, activity status of the household's head and his/her spouse.

additional year spent in education increases the likelihood of being currently at school by between 1.7% and 2.4%. The inverse Mills ratio of the credit regime selection rule (IMR1) exerts a significant effect only for the unconstrained sample, with a negative coefficient of -7.7%. This suggests the presence of unobserved variables which increase the probability of selection into the unconstrained credit regime and the probability of a lower than average score in the probability of school enrolment.

7.2 Regression estimates on school hours

The regression estimates on the amount of school hours for children between 6 and 17 years old are presented in Tables 4 and 5.[10]

[Tables 4, 5 around here]

We included seven model specifications for the determinants of school hours in order to investigate step by step the role of risk attitudes and time preferences on child time allocation.

The results for the sample of children within liquidity constrained households show that risk attitudes, time preferences and shocks are not individually significant. Overall, unobserved characteristics affecting the likelihood of being liquidity constrained are inversely related to school hours, suggesting that the average number of weekly school hours of children living in liquidity constrained households is lower than the average potential number of hours. When risks and shocks are considered jointly (models 5 and 6), JSHOCK and JRISK exert significantly impacts on school hours (which are, respectively, negative and positive). The substantial difference between the impacts of JRISK and JSHOCK confirms that their contemporaneous consideration within the same regression is sufficient to capture the distinct roles they exert on SCHHOURS. JRISK is a proxy for household's expectations of income risks and, in turn, affects the dependent variable as a potential ex-ante risk-coping strategy; JSHOCK is a proxy for household's unexpected income shocks and affects the dependent variable as a potential ex-post risk coping strategy.

In order to further investigate the appropriateness of the distinction between JRISK and JSHOCK and between MRISK and MSHOCK, we carried out a further specification by including the overall measures of parental job-related uncertainty (as the sum of JRISK and JSHOCK) and of macro uncertainty (as the sum of MRISK and MSHOCK). Regression results of model 7 suggest that this is indeed the case. The impact of the variable JRISK+JSHOCK is now not significantly different from zero, pooling the observed opposite effects of JRISK and of JSHOCK evidenced by model 6 results. Hence, the sole introduction of JRISK+JSHOCK as a compound measure of households' labor income uncertainty may be misleading as it embeds two distinct components of income uncertainty: one referred to expected job-related risks and the other referred to unexpected job-related shocks. Differently from what found in the school enrolment equation, the number of times the household has received help in the form of money, goods or services from persons outside the household or from other parties during the past 12 months (RECASSIST) is significantly and positively related to the amount of school hours.

Differently from the previous estimation results, our findings for the sample of children living in non liquidity constrained households show that, across all the specification models, path dependence

[10] Additional control variables: number of children in the household, household's size, highest level of child's education, completed grade within the highest level of child's education, household's wealth, education of the household's head and his/her spouse, acitivity status of the household's head and his/her spouse.

in child time allocation (being at school last year and the number of years the child has been enrolled at school) and the selectivity correction factors (IMRU1, IMRU2) represent the most relevant determinants of school investments.

In model specification 2, time preferences and risk attitudes appear significant: household's head impatience exerts a positive effect on the dependent variable, while risk aversion induces parents to invest less in early education. Moving to models 3 to 5, it can be noticed that JRISK and JSHOCK are the only proxies for labor income uncertainty to be significantly related to the outcome (with a positive and negative coefficient, respectively). As in the constrained sample, regression results of model 7 suggest that the distinction between JRISK and JSHOCK is appropriate as the non significant (and almost null) impact of the variable JRISK+JSHOCK pools the significant opposite effects of JRISK and JSHOCK evidenced by models 5 and 6. Hence, again, the sole introduction of JRISK+JSHOCK as a compound measure of households' labor income uncertainty may be misleading as it embeds two distinct concepts: job-related risks and unexpected job-related shocks.

To verify hypotheses *[Hp.2]* and *[Hp.5]*, we add interaction terms between our measures of macro and idiosyncratic risks and shocks to model 6 specification. Results are presented in Table 6.[11]

[Table 6 around here]

Goodness of fit measures indicate that the estimated models fit the data reasonably well: the R-squared statistics for the constrained and unconstrained sample are 0.29 and 0.20 respectively. The significance of the coefficients of correlation between the selection equations and the school investment function (IMR1 and IMR2) indicates that sample selections effectively occur.

The regression estimate on school hours for children living in liquidity constrained households shows that, after controlling for the sample selection and endogeneity issues (through the introduction of the inverse Mills ratios, IMR1 and IMR2, among the regressors), demographic characteristics are no longer highly significant compared to measures of income uncertainty, risk attitudes and time preferences.

In absence of risks and shocks, household's head risk aversion reduces the number of school hours (as shown by the negative coefficients of HRISKAV and MRISKAV). When parents are not risk averse, any macroeconomic shock affecting land crops increases the predicted number of school hours by 4 (that is 25.968-21.533).[12] This effect decreases by over 1 hour when parents are risk averse (that is 11.707-12.931). Moreover, in absence of risk aversion, job related risks and shocks (JRISK, JSHOCK) exert no significant impact, while a one point increase in cross-households income uncertainty (HINCM) reduces the predicted number of weekly school hours by 22.

The picture relevantly changes for risk averse households. First of all, job-related shocks (JSHOCK) turn out to significantly lower school hours for children whose household's head is risk averse. Hence, our *[Hp.5]* is verified and child labor acts as an initial buffer against those shocks. Moreover, when parents are risk averse, job-related risks (JRISK) and overall income uncertainty (HINCM) significantly increase the number of hours children spend at school. In particular, an inverse-U-shaped relationship can be observed between the dependent variable and the degree of household's head risk aversion. These findings verify our *[Hp.2]*, by suggesting the presence of a precautionary demand for education

[11] Additional control variables: number of children in the household, household's size, highest level of child's education, completed grade within the highest level of child's education, household's wealth, education of the household's head and his/her spouse, acitivity status of the household's head and his/her spouse.

[12] This result is apparently odd. However, it can be reasonably thought that, after adverse events on agricultural business, less time and effort in harvest activities (and hence, less child labor) is required.

from income risks especially for children whose household's head is characterized by a moderate degree of risk aversion. Instead household's head impatience does not seem to significantly affect school investments, thereby not verifying *[Hp.3]* predictions. Moreover, interactions between wealth, risk aversion and income uncertainty show that the school hours response to the interactions between income uncertainty and risk attitudes is sensible to marginal changes in household wealth and the precautionary demand for education is prevalent among wealthier households (thereby, confirming *[Hp.4]*).

The regression results on school hours for children living in non-liquidity constrained households differ substantially from those for liquidity constrained households. After controlling for sample selection and endogeneity issues (through the significant impacts of the inverse Mills ratios, IMRU1 and IMRU2), child's individual and household characteristics not related to risk preferences remain the sole relevant determinants of the number of school hours. Indeed, contrarily to what found for the constrained sample, our proxies for path dependence in child's time use represent the most relevant determinants of school investments. Being at school during the previous year and any additional year spent in education significantly increase the current number of school hours. Interactions between our measures of risks and risk attitudes are not significantly related to the dependent variable, suggesting that there is no evidence of a precautionary demand for education. This result confirms our model's prediction according to which a precautionary demand for education typically arises as a consequence of liquidity constraints and parents' risk aversion *[Hp.2]*. Similarly, interactions between our measures of shocks and risk attitudes do not exert any significant role, thereby confirming that child labor is used as an ex-post risk coping strategy by risk averse households only when borrowing possibilities are precluded (*[Hp.5]*).

Instead, in absence of risk aversion, the occurrence of adverse idiosyncratic income shocks (JSHOCK) and uncertainty in job prospects (JRISK) seems to significantly affect the number of school hours (with negative and positive coefficients, respectively). Finally, household's head time impatience exerts a positive impact on school investments by increasing the number of school hours.

The last three columns of Table 6 present the results of the Neuman-Oaxaca decomposition (2002), which is employed to decompose the effect of credit regime on the number of school hours in differences attributable to explanatory variables (explained component) and behavioral differences (unexplained component).

In this application, gaps in endowments and coefficients account for the great bulk of the gap in outcomes. The gap in endowments is mostly driven by the between-samples differences in the selectivity correction factors; the gap in coefficients is mostly due to between-groups differences in the returns to past investments in education (PREVSCH) and to the interactions between risk attitudes and risk measures.

As support of our previous findings and model predictions, the between-groups differences in the coefficients of the variables MRISKAV×JRISK, HRISKAV×JRISK and MRISKAV×HINCM, HRISKAV×HINCM are significantly negative. This result confirms that job-related risks and overall income uncertainty increase school investments of risk averse parents who are liquidity constrained to a larger extent. This between-groups gap is more pronounced at increasing degree of risk aversion. The significant positive difference in the coefficients of MRISKAV×JSHOCK and HRISKAV×JSHOCK between the two subsamples suggests that the occurrence of adverse idiosyncratic income shocks seems to exert a larger negative effect on the school hours of the disadvantaged sample.

Overall, these results confirm that the phenomenon of a precautionary demand for education is more relevant among liquidity constrained households. At the same time, the reduction in school investments as an ex-post risk coping strategy is predominantly used by risk averse parents who are liquidity constrained.

8 Conclusions

Using the Indonesia Life Family Survey dataset, this paper has shown that the determinants of child time allocation decisions significantly differ according to households' borrowing possibilities.

Though this evidence has been widely explored in the literature, this paper adds that the presence of liquidity constraints affects the joint impact of risk attitudes, income risks and shocks on schooling investments. When households are liquidity constrained, the weekly amount of hours children spend at school is found to be positively related to the interactions between risk attitudes and expected income risks.

This result suggests that a precautionary demand for education typically arises as a consequence of both liquidity constraints and risk aversion. When borrowing is precluded, risk averse parents are found to invest in schooling as a substitute for the optimal amount of precautionary savings so to insure future consumption through higher returns from their children's work. At the same time, our results point out that the lack of market insurance mechanisms against the contemporaneous realizations of adverse income shocks induces risk averse parents to underinvest in schooling and to increase the time children spend at work as an ex-post risk coping strategy.

No precautionary demand for education has been found in the face of expected macroeconomic risks, suggesting that the prospect of community-level risks is sufficient to trigger no ex-ante and ex-post risk coping strategy based on child time allocation.

Our results are supported by Belzil and Hansen (2004) and Gould, Moav, Weinberg (2001) who find that a counterfactual increase in risk aversion increases educational attainment as a safeguard strategy. Their findings however do not control for any possible variation in this response due to capital markets conditions and to the source of expected risks.

The role of riskiness in human capital investments deserves further research.

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Variable	Name	Obs	Mean	St.D.	Min	Max
school hours	schhours	6670	19.56	11.37	1	40
at school	atschool	7405	0.90	0.30	0	1
at school last year	prevsch	7405	0.84	0.37	0	1
years at school	yearssch	7405	3.49	2.24	0	9
attending elementary educ.	elementary	7405	0.73	0.45	0	1
attending junior high educ.	juniorhigh	7405	0.20	0.40	0	1
grade of level of educ.	grade	6895	2.79	1.88	0	7
age	age	7405	9.76	2.58	6	17
male	male	7405	0.52	0.50	0	1
# children in the household	nchild	7405	1.69	0.80	1	5
household's size	hsize	7405	6.72	3.00	1	39
province of residence	province	7405	34.78	16.24	12	76
rural	rural	7405	0.51	0.50	0	1
household's head impatience	hhimpatience	7405	0.83	0.37	0	1
household's head moderate risk aversion	mriskav	7405	0.10	0.30	0	1
household's head high risk aversion	hriskav	7405	0.69	0.46	0	1
household's head risk aversion	riskav	7405	1.79	0.41	1	2
household's macro risks	mrisk	7405	0.04	0.22	0	2
household's macro shocks	mshock	7405	0.09	0.31	0	3
household's crop loss	croploss	7405	0.06	0.23	0	1
household's head job risks	jrisk	7405	1.24	2.52	0	7
household's head job shocks	jshock	7405	0.44	0.74	0	2
household's income uncertainty	hincmcv	7193	0.05	0.20	0	2
being liquidity constrained	liqcons	7405	0.12	0.33	0	1
household's wealth index	wealth	7405	0.45	0.91	-6	3
wealth percentile 1	wealthpc1	7405	0.33	0.47	0	1
wealth percentile 2	wealthpc2	7405	0.33	0.47	0	1
wealth percentile 3	wealthpc3	7405	0.33	0.47	0	1
household's head educ.	hheduc	7405	2.53	0.76	1	4
education of spouse of household's head	speduc	7405	2.00	1.04	0	3
household's head unemployed	hhunempl	7405	0.72	0.45	0	1
household's head dependent work	hhdependent	7405	0.03	0.16	0	1
household's head self-employed	hhselfempl	7405	0.19	0.39	0	1
household's head casual worker	hhcasualwk	7405	0.07	0.25	0	1
spouse of household's head unemployed	spunempl	7405	0.90	0.31	0	1
spouse of household's head dependent work	spdependent	7405	0.01	0.08	0	1
spouse of household's head self-employed	spselfempl	7405	0.04	0.19	0	1
spouse of household's head casual work	spcasualwk	7405	0.06	0.24	0	1
# employed adults in the household	ademployed	7405	1.27	0.98	0	7
# times the household provided assistance	givassist	7405	0.98	1.29	0	12
# times the household received assistance	recassist	7405	1.97	2.31	0	12

Table 1: Variables definitions and summary statistics.

SI01 Which option will you choose?	1. Guaranteed Rp 2 million 2. Equal chance of Rp 4 mil. or Rp 2 mil. → SI03
SI02 Are you sure?	1. Still picks option 1 (go to SI11) 2. Switches to option 2
SI03 Which option will you choose?	1. Guaranteed Rp 2 million 2. Equal chance of Rp 4 mil. or Rp 1 mil. → SI05
SI04 Which option will you choose? → SI11	1. Guaranteed Rp 2 million per month 2. Equal chance of Rp 4 mil. or Rp 1,5 mil.
SI05 Which option will you choose? → SI11	1. Guaranteed Rp 2 million 2. Equal chance of Rp 4 million or Rp 500.000
SI11 Which option will you choose?	1. Guaranteed Rp 10 million → SI13 2. Equal chance of Rp 10 mil. or Rp 5 mil.
SI12 Are you sure?	1. Still picks option 1 → SI21 2. Switches to option 2
SI13 Which option will you choose?	1. Guaranteed Rp 10 million 2. Equal chance of Rp 30 mil. or Rp 0 → SI15
SI14 Which option will you choose?	1. Guaranteed Rp 10 million 2. Equal chance of Rp 20 mil. or Rp 5 mil.
SI15 Which option will you choose?	1. Guaranteed Rp 10 million 2. Equal chance of Rp 40 mil. or Rp 5 mil.
SI21A You can choose between	1. Rp 1 mil. today 2. Rp 1 million in 1 year
SI21B You can choose between	1. Rp 1 million today 2. Rp 3 million in 1 year
SI21C You can choose between	1. Rp 1 million today 2. Rp 6 million in 1 year
SI21D You can choose between	1. Rp 1 million today 2. Rp 2 million in 1 year
SI21E Are you sure you prefer to wait?	1. Yes 3. No prefer Rp 1 million today

Table 2: Lotteries.

	(1)	(2)	(3)
	Pr(liq_cons)>0	Pr(at_school)>0	Pr(at_school)>0
		liq_cons=1	liq_cons=0
age		-0.029***	-0.018***
		(0.006)	(0.002)
male		-0.001	-0.004
		(0.012)	(0.003)
# children in the household	0.015***	-0.004	-0.001
	(0.004)	(0.008)	(0.002)
household's size	0.003***	-0.001	0.001
	(0.001)	(0.002)	(0.001)
household's head sec. educ.	-0.043***	0.032	-0.007
	(0.012)	(0.028)	(0.008)
household's head tert. educ.	-0.089***	0.033	-0.009
	(0.012)	(0.031)	(0.010)
household's head other educ.	-0.092***	0.036***	-0.016
	(0.007)	(0.012)	(0.017)
at school last year		0.607***	0.523***
		(0.057)	(0.028)
# years at school		0.024***	0.017***
		(0.007)	(0.002)
rural	0.038***	-0.010	0.002
	(0.008)	(0.020)	(0.004)
wealth percentile 2	-0.035***	0.003	-0.004
	(0.008)	(0.020)	(0.004)
wealth percentile 3	-0.038***	0.008	-0.007
	(0.008)	(0.020)	(0.005)
assistance received (recassist)	0.002	-0.000	-0.001
	(0.002)	(0.003)	(0.001)
IMR1		-0.059	-0.077***
		(0.078)	(0.027)
assistance provided (givassist)	-0.020***		
	(0.004)		
N		902	6,503
Pseudo R2	0.123	0.517	0.519

Table 3: Selection equations. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
at school last year	-7.129*	-7.042*	-6.755*	-7.135*	-7.282*	-7.228**	-7.061*
	(3.834)	(3.694)	(3.914)	(3.819)	(3.803)	(3.660)	(3.662)
years at school	-0.196	-0.298	-0.970	0.031	-0.207	-0.324	-0.295
	(1.566)	(1.569)	(1.585)	(1.560)	(1.570)	(1.566)	(1.572)
recassist	0.546***	0.563***	0.567***	0.533***	0.562***	0.583***	0.573***
	(0.206)	(0.208)	(0.206)	(0.205)	(0.204)	(0.207)	(0.209)
hhimpatience		2.697**				3.495**	3.161**
		(1.314)				(1.425)	(1.408)
mriskav		-3.293*				-2.831	-3.066
		(1.933)				(1.971)	(1.946)
hriskav		-1.868*				-1.464	-1.625
		(1.113)				(1.148)	(1.127)
mrisk			-1.755		-2.440	-2.416	
			(2.188)		(2.215)	(2.188)	
jrisk			0.029		0.662**	0.728***	
			(0.172)		(0.272)	(0.273)	
hincm			-0.957		-1.618	-1.653	
			(1.856)		(1.884)	(1.917)	
mshock				1.072	0.972	1.367	
				(2.903)	(2.951)	(2.900)	
croploss				0.989	1.104	0.533	
				(3.367)	(3.419)	(3.361)	
jshock				-0.590	-2.811***	-2.586***	
				(0.539)	(0.912)	(0.922)	
mrisk+mshock							-0.399
							(1.688)
jrisk+jshock							0.140
							(0.148)
N	784	784	746	784	746	746	784
R2	0.227	0.233	0.238	0.230	0.251	0.259	0.234

Table 4: School hours regression equations under liquidity constraints. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
at school last year	4.332***	4.344***	3.941***	4.337***	3.928***	3.934***	4.340***
	(1.189)	(1.187)	(1.179)	(1.190)	(1.163)	(1.158)	(1.186)
years at school	1.014**	1.013**	0.971**	1.025**	1.013**	1.004**	1.009**
	(0.413)	(0.413)	(0.415)	(0.410)	(0.407)	(0.407)	(0.413)
recassist	0.344***	0.335***	0.344***	0.321***	0.340***	0.334***	0.332***
	(0.068)	(0.069)	(0.069)	(0.068)	(0.069)	(0.069)	(0.069)
impatience		0.970**				0.729	0.826*
		(0.412)				(0.452)	(0.445)
mriskav		-0.347				-0.422	-0.445
		(0.520)				(0.529)	(0.528)
hriskav		-0.889**				-1.045***	-0.982**
		(0.373)				(0.386)	(0.384)
mrisk			0.335		0.078	0.132	
			(0.689)		(0.708)	(0.710)	
jrisk			0.015		0.598***	0.590***	
			(0.064)		(0.097)	(0.098)	
hincm			-0.001		-0.012	-0.036	
			(0.702)		(0.702)	(0.703)	
mshock				-0.342	-0.467	-0.458	
				(0.734)	(0.741)	(0.743)	
croploss				0.908	0.971	1.014	
				(0.996)	(1.011)	(1.013)	
jshock				-1.036***	-2.661***	-2.674***	
				(0.201)	(0.321)	(0.324)	
mrisk+mshock							0.125
							(0.482)
jrisk+jshock							-0.050
							(0.056)
N	5,870	5,870	5,713	5,870	5,713	5,713	5,870
R2	0.180	0.181	0.181	0.184	0.192	0.193	0.181

Table 5: School hours regression equations under no liquidity constraints. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

	liq_cons=0	liq_cons=1	Differences		
N	5,713	746	Endowments	Coefficients	Interaction
Predictions	19.650***	18.862***	-8.367***	7.218***	1.937
mriskav	-0.454	-3.885*	-0.223**	0.298*	0.206*
	(0.621)	(2.293)	(0.109)	(0.152)	(0.111)
hriskav	-1.085**	-1.924	0.097	0.247	-0.014
	(0.460)	(1.419)	(0.073)	(1.133)	(0.066)
mrisk	-1.379	15.102**	-0.024	-0.506	0.027
	(3.431)	(6.382)	(0.085)	(0.492)	(0.096)
mshock	-2.410	-21.533*	-0.141	1.430	0.140
	(2.839)	(11.028)	(0.241)	(1.416)	(0.242)
croploss	-0.607	25.968**	-0.114	-1.259	0.115
	(4.218)	(13.191)	(0.217)	(1.187)	(0.221)
jrisk	0.570**	-1.020	0.287	2.679***	-0.390
	(0.269)	(1.077)	(0.209)	(1.029)	(0.257)
jshock	-2.317**	2.488	-0.142	-2.802**	0.230
	(0.931)	(3.820)	(0.153)	(1.288)	(0.215)
hincm	-1.267	-22.216***	-0.129	1.295**	0.124
	(1.762)	(6.232)	(0.214)	(0.511)	(0.206)
riskav×mrisk	1.249	-9.084	0.038	0.660	-0.044
	(1.816)	(5.560)	(0.111)	(0.532)	(0.127)
riskav×mshock	1.114	11.707*	0.141	-1.426	-0.143
	(1.603)	(6.197)	(0.239)	(1.324)	(0.244)
riskav×croploss	0.899	-12.931*	0.074	1.122	-0.080
	(2.326)	(7.453)	(0.181)	(1.107)	(0.194)
mriskav×jrisk	-0.294	2.933*	0.016	-0.168*	-0.019
	(0.406)	(1.517)	(0.060)	(0.090)	(0.072)
hriskav×jrisk	0.119	2.309**	-0.387*	-1.875***	0.410*
	(0.313)	(1.133)	(0.228)	(0.641)	(0.241)
mriskav×jshock	-0.184	-10.203**	-0.084	0.177*	0.095
	(1.292)	(4.655)	(0.072)	(0.099)	(0.079)
hriskav×jshock	-0.547	-5.217	0.275	1.726**	-0.271
	(0.995)	(3.935)	(0.195)	(0.809)	(0.197)
mriskav×hincm	2.065	32.280***	0.078	-0.164*	-0.073
	(2.308)	(7.790)	(0.088)	(0.092)	(0.083)
hriskav×hincm	-0.049	15.346**	-0.070	-0.846*	0.070
	(2.191)	(6.850)	(0.149)	(0.450)	(0.150)
hriskav×hincm×wealthpc2	2.619	9.638**	0.050	-0.070	-0.039
	(2.104)	(4.765)	(0.045)	(0.059)	(0.041)
hriskav×hincm×wealthpc3	1.556	7.943*	-0.036	-0.112	0.029
	(1.870)	(4.164)	(0.043)	(0.100)	(0.039)
R2	0.195	0.289			

Table 6: Determinants of school hours. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

A The econometric model

The model is specified as follows:

$$\begin{aligned}
\text{Credit regime affiliation rule} \quad : \quad & y_{1i}^* = \mathbf{x}_{1i}'\boldsymbol{\beta}_1 + u_{1i} && \text{(A.1)} \\
\text{School enrolment affiliation rule:} \quad & y_{2i}^* = \mathbf{x}_{2i}'\boldsymbol{\beta}_2 + u_{2i} && \text{(A.2)} \\
\text{Hours at school:} \quad & y_{3i} = \mathbf{x}_{3i}'\boldsymbol{\beta}_3 + \sigma_3 u_{3i} && \text{(A.3)}
\end{aligned}$$

Let our dependent variable, namely the number of hours the i-th child spent at school during the last week or the last week the school was in session, be identified by y_{3i}.The response y_i of the ith individual from a random sample $N = \{1, ..., n\}$ is assumed to depend on a $K \times 1$ vector of explanatory variables (including the constant term), $\mathbf{x}_{3i}$, with $\boldsymbol{\beta}$ representing the related $K \times 1$ vector of parameters to be estimated. σ_3 is an unknown scale parameter, and the u_{mi}'s (with m from 1 to 3) are the unobserved terms with zero means and the following correlation matrix:

$$\Sigma = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix}$$

The selection variables, y_{1i}^* and y_{2i}^*, representing the likelihoods for a child to belong to a liquidity constrained household and to be enrolled in school respectively, are not observed. Only their signs are observed, i.e. whether or not a child belongs to a liquidity constrained household and whether or not she is enrolled in school. Thus, the variances of the unobserved terms in the selection equations cannot be estimated and are set to one. The binary variables D_1 and D_2 are the observed outcomes of the selection rules and allow classification of the sample following:

$$D_1 = \begin{matrix} 1 \text{ if } y_1^* > 0 \\ 0 \text{ if } y_1^* \leq 0 \end{matrix} \tag{A.4}$$

$$D_2 = \begin{matrix} 1 \text{ if } y_2^* > 0 \\ 0 \text{ if } y_2^* \leq 0 \end{matrix} \tag{A.5}$$

As a result of the two selection rules, four possible outcomes can occur:

1. $(D_1 = 1, D_2 = 1)$, living in a liquidity constrained household and being enrolled in school;
2. $(D_1 = 1, D_2 = 0)$, living in a liquidity constrained household and not being enrolled in school;
3. $(D_1 = 0, D_2 = 1)$, not living in a liquidity constrained household and being enrolled in school;
4. $(D_1 = 0, D_2 = 0)$, not living in a liquidity constrained household and not being enrolled in school.

To account for the possible presence of sample selection biases (discussed above), we choose to split up the whole sample into two sub-sample: one including children living in liquidity constrained households (denoted by C) and the other including children living in non-liquidity constrained households (denoted by U).

To proceed we estimate the probit for credit regime affiliation first for the whole sample and then generate the Inverse Mill's Ratio (IMR) term for each sub-sample. These terms will then be included in the probit equation explaining enrolment status for each sub-sample. The appropriate IMR terms from these equations would then be included in the two final schooling hours equations for each subsample (Amemiya 1985). Hence, formally, for each subsample, we would end up with only three observed (out of four) outcomes.

For the liquidity constrained sample:

1. $(D_1 = 1, D_2 = 1)$, living in a liquidity constrained household and being enrolled in school;

2. $(D_1 = 1, D_2 = 0)$, living in a liquidity constrained household and not being enrolled in school;

For the non-liquidity constrained sample:

1. $(D_1 = 0, D_2 = 1)$, not living in a liquidity constrained household and being enrolled in school;

2. $(D_1 = 0, D_2 = 0)$, not living in a liquidity constrained household and not being enrolled in school.

With this structure, the regression function for the equation of interest for each subsample is:

$$E\left(y_{3i}|\mathbf{x}_{3i}, D_1, D_2\right) = \mathbf{x}_{3i}'\boldsymbol{\beta}_3 + \sigma_3 E\left(u_{3i}|\mathbf{x}_{3i}, D_1, D_2\right) \tag{A.6}$$

If $E\left(u_{3i}|\mathbf{x}_{3i}, D_1, D_2\right) \neq 0$, then a linear regression of y_{3i} on $\mathbf{x}_{3i}$ will result in biased parameter estimates. In order to generate unbiased estimates of the elements of $\boldsymbol{\beta}_3$, additional information regarding the conditional distribution of the unobserved term, u_{3i}, is required. The additional structure imposed here is the form of the joint distribution of the three unobserved terms. Assume $(u_{1i}, u_{2i}, u_{3i}) \sim N(0, \Sigma)$, independent of the observation of the covariates. For a same individual, however, the unobserved terms may be correlated.

For the liquidity constrained subsample, school hours are observed only when $y_{1i}^* > 0$ and $y_{2i}^* > 0$. Then, for this subsample, the conditional expectation of y_{3i} is:

$$E\left(y_{3i}^c|\mathbf{x}_{3i}^c, D_1, D_2\right) = \mathbf{x}_{3i}'^c\boldsymbol{\beta}_3^c + \sigma_3^c E\left(u_{3i}^c|u_{1i} > -\mathbf{x}_{1i}'\boldsymbol{\beta}_1, u_{2i} > -\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right) \tag{A.7}$$

The multivariate normal structure allows the derivation of an expression for the conditional expectation of the disturbance, u_{3i}:

$$E\left(u_{3i}^c|u_{1i} > -\mathbf{x}_{1i}'\boldsymbol{\beta}_1, u_{2i} > -\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right) = \rho_{13}^c\lambda_1^c + \rho_{23}^c\lambda_2^c \tag{A.8}$$

where the two lambda terms are the analogues to the selection inverse Mill's ratio. With these results, the conditional expectation in A.7 becomes:

$$E\left(y_{3i}^c|\mathbf{x}_{3i}^c, D_1, D_2\right) = \mathbf{x}_{3i}^{\prime c}\boldsymbol{\beta}_3^c + \theta_1^c\lambda_1^c + \theta_2^c\lambda_2^c \tag{A.9}$$

where $\theta_1^c = \sigma_3^c\rho_{13}^c$, $\theta_2^c = \sigma_3^c\rho_{23}^c$.

Similarly, for the liquidity unconstrained subsample, school hours are observed only when $y_{1i}^* \leq 0$ and $y_{2i}^* > 0$. Then, for this subsample, the conditional expectation of y_{3i} is:

$$E\left(y_{3i}^u|\mathbf{x}_{3i}^u, D_1, D_2\right) = \mathbf{x}_{3i}^{\prime u}\boldsymbol{\beta}_3^u + \sigma_3^u E\left(u_{3i}^u|u_{1i} > -\mathbf{x}_{1i}'\boldsymbol{\beta}_1, u_{2i} > -\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right) \tag{A.10}$$

The multivariate normal structure allows the derivation of an expression for the conditional expectation of the disturbance, u_{3i}:

$$E\left(u_{3i}^u|u_{1i} > -\mathbf{x}_{1i}'\boldsymbol{\beta}_1, u_{2i} > -\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right) = \rho_{13}^u\lambda_1^u + \rho_{23}^u\lambda_2^u \tag{A.11}$$

where the two lambda terms are the analogues to the selection inverse Mill's ratio, with $\lambda_2^u = \frac{\varphi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right)}{\Phi\left(\mathbf{x}_{2i}'\boldsymbol{\beta}_2\right)}$, and $\lambda_1^u = \frac{\varphi\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1\right)}{\Phi\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1\right)}$. With these results, the conditional expectation in A.10 becomes:

$$E\left(y_{3i}^u|\mathbf{x}_{3i}^u, D_1, D_2\right) = \mathbf{x}_{3i}^{\prime u}\boldsymbol{\beta}_3^u + \theta_1^u\lambda_1^u + \theta_2^u\lambda_2^u \tag{A.12}$$

where $\theta_1^u = \sigma_3^u\rho_{13}^u$, $\theta_2^u = \sigma_3^u\rho_{23}^u$.

The estimation is conducted in two steps. First, data on the outcomes of the two selecting rules are used to obtain the likelihood function for the bivariate probit. Letting $F(\cdot)$ denote the standard normal cumulative distribution functions, this likelihood function is:

$$\begin{aligned} L \quad = \quad & \prod_{\substack{D_1=0\\D_2=1}} F\left(-\mathbf{x}_{1i}'\boldsymbol{\beta}_1, \mathbf{x}_{2i}'\boldsymbol{\beta}_2; -\rho_{12}\right) \cdot \prod_{\substack{D_1=1\\D_2=1}} F\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1, \mathbf{x}_{2i}'\boldsymbol{\beta}_2; \rho_{12}\right) \cdot \\ & \cdot \prod_{\substack{D_1=0\\D_2=0}} F\left(-\mathbf{x}_{1i}'\boldsymbol{\beta}_1, -\mathbf{x}_{2i}'\boldsymbol{\beta}_2; \rho_{12}\right) \cdot \prod_{\substack{D_1=1\\D_2=0}} F\left(\mathbf{x}_{1i}'\boldsymbol{\beta}_1, -\mathbf{x}_{2i}'\boldsymbol{\beta}_2; -\rho_{12}\right) \end{aligned} \tag{A.13}$$

The first term of the likelihood function corresponds to children living in non-liquidity constrained households who are enrolled in school; the second term to children living in liquidity constrained households who are enrolled in school; the third term to children living in non-liquidity constrained households who are not enrolled in school; the last term to children living in liquidity constrained households who are not enrolled in school. Maximum likelihood estimation of 15 yields consistent estimates of $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2$ and ρ_{12}. These parameter estimates are used to construct $\hat{\lambda}_1$and $\hat{\lambda}_2$ for each child, either living in liquidity constrained households and not living in liquidity constrained households. These can be inserted into A.9 and A.12 to yield the selection corrected school hours equations:

$$E\left(y_{3i}^{u}|\mathbf{x}_{3i}^{u},D_1,D_2\right) = \mathbf{x}_{3i}^{\prime u}\boldsymbol{\beta}_3^u+\theta_1^u\hat{\lambda}_1^u+\theta_2^u\hat{\lambda}_2^u+\sigma_3^u v_3^u \quad \text{(A.14)}$$

$$E\left(y_{3i}^{c}|\mathbf{x}_{3i}^{c},D_1,D_2\right) = \mathbf{x}_{3i}^{\prime c}\boldsymbol{\beta}_3^c+\theta_1^c\hat{\lambda}_1^c+\theta_2^c\hat{\lambda}_2^c+\sigma_3^c v_3^c \quad \text{(A.15)}$$

with $E\left(v_3^u|D_1=0,D_2=1\right)=0$ and $E\left(v_3^c|D_1=1,D_2=1\right)=0$. Equations A.14 and A.15 are fitted by ordinary least squares. Estimates of the correlation coefficients ρ_{12} and ρ_{23} are obtained by solving for θ_1,θ_2.