Student Paper

Young Lives

An International Study of Childhood Poverty

NREGs – Correcting for the 'Accident' of Birth? A Study of the Determinants of Risk Aversion in Andhra Pradesh, India

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Paper submitted in partial fulfillment of the requirements for the Degree of Master of Science in Economics for Development at the University of Oxford.

The data used come from Young Lives, a longitudinal study of childhood poverty that is tracking the lives of 12,000 children in Ethiopia, India (Andhra Pradesh), Peru and Vietnam over a 15-year period. **www.younglives.org.uk**

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NREGS – CORRECTING FOR THE 'ACCIDENT' OF BIRTH?

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By

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Abstract

Economic literature has established the importance of risk attitudes in economic decision making. The study examines determinants of risk aversion in children. It also explores the potential of the government to mitigate the effect of shocks, by looking at the effectiveness of the world's largest public works program – National Rural Employment Guarantee Scheme (NREGS). First, it builds a general model of the determinants of childhood risk aversion. The study finds that the environment – economic and psychological, that a child is born into plays an important role in developing the non-cognitive skill - preference for risk. Additionally, economic shocks do not have a significant impact on risk aversion in childhood years *vis-a vis* psychological trauma. Second, the study investigates whether NREGS has been effective in smoothing income shocks for rural households as would be reflected by less risk averse children. NREGS has been effective in providing a stable environment to children resulting in lower risk aversion. Access to the scheme reduced risk aversion in the Indian sample by 36- 43%. The study employs OLS and Probit models using Young Lives Round 3 (2009-10) cross-section data from Andhra Pradesh, India, since the risk questions were only asked in that round. Identification is difficult using only cross-section data, so I am only able to establish correlations. Further, the Young Lives dataset contains a rich set of control variables, and Propensity Matching is used to correct for self-selection into the NREGS. A series of reliability test have also been conducted to ensure the robustness of results.

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I. INTRODUCTION

Risk and uncertainty play an important role in economic decision making. If people were risk neutral or if one could perfectly insure against all risks through well-developed credit and insurance markets, one would not have to be concerned about such an analysis. However, empirical literature reveals high risk aversion among individuals. Harrison, Humphrey and Verschoor (2005) estimate a risk aversion measure of 0.84 for their Indian sample under the Expected Utility framework, implying a high degree of risk aversion. As a consequence, in order to understand and predict economic behaviour, understanding individual risk attitudes is primary. More importantly, one has to understand the development of risk attitudes through various stages of life. Cognitive and non-cognitive skills (risk aversion) begin to take shape in early childhood years. The 'accident' of being born into a disadvantaged environment that does not cultivate cognitive and non-cognitive abilities can place a child at a disadvantage (Heckman, 2000). Since risk attitude is an important determinant of educational attainment and occupational choice in adulthood, impoverished early environment, resulting in severely risk averse individuals, becomes a strong predictor of adult failure on various economic dimensions. A body of research in economics and psychology shows that skill begets skill (Heckman, 2006). Children who develop extreme risk aversion are likely to remain so. Hence, it becomes important to study what drives risk behaviour in early years of growing up and also the need for early intervention to protect the children from adversities.

In this light, I attempt to study the factors that shape risk attitudes during the critical period of early childhood. In my sample, 91% of the Indian households identify themselves as poor holding a Below-Poverty-Line (BPL)[1] card. By being placed in an adverse environment, the young children in my study are more vulnerable to shocks and adversities than their richer counterparts. This paper not only looks at the determinants of risk aversion, but also the importance of different factors – psychological and economic. Interestingly, in the early years, psychological factors such as being included

[1] BPL households in India are identified as those who do not earn the minimum daily income required to meet the daily calorie norms of 2400 calorie in rural areas and 2100 calorie in urban areas.

in games with peers and death of a family member have a significant impact on risk attitudes.

The second part of the paper analyses the effect of being covered by social protection on risk aversion in children, while controlling for other household and individual characteristics. One of the main arguments for social protection is to help the poor cope with risk in the absence of well-developed insurance and credit markets. The poor are vulnerable to income shocks which move them in and out of poverty. The National Rural Employment Scheme (NREGS) is a public works program in India which corrects for cyclical unemployment, by providing the rural households with employment and income opportunities. This ensures that the households registered under the program are protected from income shocks and are able to smooth income and consumption. I hypothesise that a household which is able to do so will result in less risk averse children. These children are able to correct for their 'accident' of birth as they are less likely to be exposed to shocks such as, being taken out of school and drop in the nutritional value of their diet. Results from this study show that households covered by the NREGS have less risk averse children. This result is important with two regards. First, it establishes the need for public intervention to mitigate the impact of a disadvantaged environment. Second, it establishes the effectiveness and success of NREGS in helping the rural households to protect themselves from shocks.

The paper is organised as follows. Section II describes the relevant research that has been undertaken around determinants of risk aversion and impact of NREGS, highlighting the specific contribution of this paper. Section III builds on a theoretical model of determinants of childhood risk aversion. Section IV gives a brief overview of the social protection scheme, NREGS. Section V briefly describes the data used in the study and the lottery game that was played with the children in the sample. Section VI presents the summary statistics. Section VII describes the econometric model and the empirical strategy employed. Section VIII presents the empirical results and reliability tests, and Section IX concludes the paper, emphasizing on the findings.

II. RELEVANT RESEARCH

Considerable research has attempted to explain the factors affecting individuals' risk attitudes. Dohmen *et al* (2011) find that gender, age, height, and parental background have an economically significant impact on willingness to take risks. Wealth has been found to have a significant effect on risk aversion in Mette Wik *et al* (2004). They also find that females are more risk averse than males in general. Guiso and Paiella (2008) report that individuals who are exposed to background risks, that is, those who are more likely to become liquidity constrained or face income uncertainty exhibit a higher degree of risk aversion. However, these studies focus on risk attitudes in adults. To my knowledge, there is no relevant research conducted with younger age groups in the area of risk attitudes. Also, there is scant literature on capturing the effect of social security schemes or policies in general on risk behaviour. One example is, Hryshko *et al* (2011) which shows that policy induced increases in high school graduation rates lead to significantly fewer individuals being highly risk averse in the next generation.

Dercon (2006) argues that uninsured risk increases poverty through ex ante behavioural responses affecting activities, assets and technology choices; as well as ex post through loss of productive assets. He concludes on the basis of this discussion that there is a case for risk-focussed social protection. Social protection schemes, of which NREGS is one, provide ex post measures to the poor when they are faced with an adverse shock and remain uninsured. Given their low income and low assets, the poor are more vulnerable to risks. At lower levels of income, people are more risk averse, as their welfare is reduced to larger extent than that of the rich. Studies in India have found that negative income shocks caused households to withdraw their children from school. This causes lower educational standards and reduces the income-earning potential of the children (Jacoby and Skoufias, 1992). Also, in my sample, only 3.8% would try to obtain credit from the formal sector in the case of hard times ("What would you do in the case of hard times?"), which can be taken to mean either a non-existent formal credit sector or little faith in the financial system. Hence, there is strong argument in favour of social protection – to help the poor cope with shocks reducing their risk aversion and to ensure proper investment in the child at the critical stage.

With regards to the welfare impact of NREGS in India on rural households, specifically children, it has been found that NREGS has had a positive effect on child health outcomes (Uppal, 2009; Dasgupta, 2012). Ravi and Engler (2009) have additionally looked at the impact of NREGS on food security and savings. Uppal (2009) reports that NREGS significantly reduced the likelihood of children in the household being required to work. The stability and increase in nutritional intake introduced by NREGS can translate into lower risk averse children as they grow up in a safer environment.

This paper makes two contributions to the literature. First, it investigates Heckman's theory of life cycle of skill development. Non-cognitive abilities such as, preference for risk are shaped at an early stage by a host of environmental factors, of which the family environment is crucial. I test this hypothesis in my sample of 1950 young children in the age group 8-9 years. To my knowledge, this is the only paper which tries to ascertain the determinants of childhood risk aversion. Second, most studies have looked at the effect of NREGS in terms of health outcomes in children. However, I look at the basic premise for the provision of social protection to comment on its effectiveness. If the NREGS successfully equipped the rural households to mitigate adverse shocks, the children would not have to suffer from the ills of child labour, withdrawal from school or inadequate diet. Thus, the effectiveness of the NREGS would be reflected in less risk averse children. The results in this paper pose interesting questions for future research - how does risk aversion behaviour change over the years and which determinants come to play a dominant role? The results also uphold and strengthen the claims of some economists – policy interventions that enrich the early years of disadvantaged children improve non-cognitive skills.

III. CONCEPTUAL FRAMEWORK – THEORY OF CHILDHOOD RISK AVERSION

Most economic literature has revolved around studying risk behaviour in adults, neglecting the sensitive childhood phase. Knudsen (2004) shows that early experience and environment create a structure of neural circuits, which cannot be altered beyond the sensitive period. Heckman (2000) builds a model of complementarity in investment in human capital, that is, early investment facilitates the productivity of later investment. Thus, it is important to study the critical childhood period to enhance our understanding of how certain attitudes are formed and how they can be adapted using policy interventions to be conducive to efficient life outcome.

I attempt to build a comprehensive model to study the determinants of one such attitude - risk aversion. Some of the determinants of risk attitudes described in empirical literature are gender, age, wealth, parental background and shocks. A study by Turkheimer *et al* (2003) found that in poor households, 60% of the variance in cognitive ability is accounted for by the shared environment. Following from this, I hypothesise that the environment, both economic and emotional, plays a similar role in the nurturing of non-cognitive skills, such as, preference for risk among children born in an economically disadvantaged environment. As suggested by Heckman *et al* (2006), it is important to study the role of family income and investment in children in determining risk attitudes. Hence, I divide the determinants of childhood risk aversion into two broad categories – economic (E_i) and psychological (P_i). Formally, risk aversion (y_i) is a function of these two and other individual level controls (X_i).

$$y_i = f(E_i, P_i, X_i)$$

One can think of economic factors in terms of income of the household the child is born into, the area of residence (rural/urban), wealth of the family, access to amenities, and main occupation pursued by the household head. Also, important to consider are economic shocks (natural disaster, drought) – shocks which produce volatility in the income flow. The psychological factors, on the other hand, provide for those factors that affect the mental functions and behaviour of the child. These factors can range from having a single parent, interaction with family members, and social inclusion to shocks such as death of a family member. The individual level characteristics control for inherent differences in preference for risk – gender and cognitive skills.

It is important to note at this stage, that there are innumerable things that affect risk attitudes and it is virtually impossible to account for all of them or perfectly predict risk behaviour. For instance, Heckman *et al* (2006) argue that skill formation begins in the womb and may be in part attributable to genes. Since there is no reliable method for measuring the effect of such factors, despite including a near exhaustive set of explanatory variables there will be unobservables in the error term driving the risk behaviour and leading to a bias in the estimated coefficients. Hence, in such a model studying risk behaviour, one can at most argue for correlation. Additionally, there may be some degree of correlation between the explanatory variables themselves. For instance, one cannot expect the wealth of the family to be entirely independent of social inclusion. A child from a wealthier background may be more accepted in his peer group. Taking these into account, I present my results as a correlation and study the likelihood of certain factors in producing more/less risk averse children.

IV. THE PROGRAM – NATIONAL RURAL EMPLOYMENT GUARANTEE SCHEME (NREGS)[2]

The NREGS program is the largest public works program in the world which came into force in February 2006. Public works programs have had numerous objectives including short term income generation, asset creation, protection from negative shocks and poverty alleviation (Ninno *et al*, 2009). The primary objective of the NREGS is to provide livelihood security to households in the rural area by providing not less than 100 days of guaranteed wage employment in every financial year to every household, whose adult members volunteer to do unskilled and manual work (GOI, 2009). The rural household would first have to be registered under the scheme. Thereafter, if the household wished to undertake work under the scheme, it would have to apply to the *Gram Panchayat*, which the *Gram Panchayat* and the State were legally bound to provide within 15 days of demand for work. Failure to do so would result in payment of unemployment allowance by the State. Thus, the scheme introduced an in-built incentive mechanism for performance on the supply side. It also incorporated time bound action to meet the demand for work.

The scheme was implemented in a phased manner, initially rolled out in 200 of the poorest districts in early 2006, making use of a backwardness index - comprising agricultural productivity per worker, agricultural wage rate, and Scheduled Caste/Scheduled Tribe population, developed by the Planning Commission. It was expanded to an additional 130 districts in 2007, and finally expanded to cover the remaining 274 districts in 2008. For Andhra Pradesh, the program was rolled out first of all to 13 districts in 2005, then to a further six districts in 2007 and three more districts

[2] The NREGS was renamed Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) on 2nd October, 2009.

in 2008, to cover all 22 districts in the state. Four of my sample districts were covered by the NREGS in the first phase of implementation in 2005-06 (Anantapur, Mahaboobnagar, Cuddapah, Karimnagar), with the addition of one more sample district (Srikakulam) in 2007, and lastly the district of West Godavari was included in 2008. During 2010–11 Andhra Pradesh provided 274.8 million person days of employment (Galab *et al*. 2011).

V. DATA AND EXPERIMENTAL DESIGN

The Young Lives Study follows approximately 3000 children – 1950 children born in 2001-02 and 994 children born in 1994-95 in the state of Andhra Pradesh in India. The Young Lives Survey has been conducted in three waves – 2001-02, 2006-07 and 2009-10. A lottery game to elicit risk behaviour was played only the third round, 2009-10, with the younger cohort (those born in 2001-02). Since I have information on risk aversion for only the last round, I am unable to exploit the benefits of a panel data and am restricted to Young Lives Round 3 cross-section data for the first part of my study, which is to build a model of childhood determinant of risk aversion. In Round 3 extensive child, household and community questionnaires were administered which enables me to include a host of controls in my regression analysis. For the second part of my analysis, which is to study the role of NREGS in mitigating the effect of adverse environment on risk attitudes, I exploit the panel data for conducting a propensity score matching on my rural sub-sample. Regarding the NREGS, households were asked whether anybody in the household had registered for the NREGS, whether anybody in the household has worked under the scheme in the last 12 months, whether employment was provided within 15 days of registration, whether wages were paid within 15 days of being employed, whether they benefited from unemployment allowance, and whether they benefited from childcare facilities at the worksite. The data was collected in Hyderabad and six districts of Andhra Pradesh, chosen to represent the different geographical regions, levels of development and population characteristics (Young Lives website), while households were chosen randomly amongst those which had children born in the stipulated years.

In Young Lives Round 3 data, risk aversion information was collected for the younger cohort in India. The children were presented with 6 options. The lottery was not played with real money as that would have been ethicallyincorrect, but the children were asked to pretend that they were dealing with real money. A coin was flipped and depending on the lottery choice of the child and whether the coin landed heads or tails, the child won an amount. With the first choice, if the coin landed on heads, the child won 50 rupees, and if it landed on tails, the child also got 50 rupees. With the second choice, if the coin landed on heads, 100 rupees was won, and if it landed on tails, only 40 rupees was won. The options have been summarised in table 5.1

Table 5.1 Lottery Game

Gamble Choice	Payoff Low	Payoff High	Expected payoff	Variance	Risk Aversion Class
1	50	50	50	0	Extreme
2	40	100	70	900	Severe
3	30	130	80	2500	Intermediate
4	20	160	90	4900	Moderate
5	10	190	100	8100	Slight to neutral
6	0	200	100	10000	Neutral to negative

Some important points to note are that there were no losses involved in the game. The expected payoff increases with the lottery choice, but so does the riskiness as measured by the variance. Lottery choices 5 and 6 present the same expected return, but lottery choice 6 entails a greater degree of risk. Hence, only a “risk loving” individual would opt for the choice. The lottery game is similar in design to Binswanger (1980, 1981) and Barr & Genicot (2008). Most studies on risk aversion have relied on survey questions which are not incentive compatible (Camerar & Hogarth, 1999). The lottery game I am dealing with in this study is an incentive compatible experimental measure, making it robust. There is a potential concern regarding the understanding of the game by the child. Since these children are in the age group 8-9 years, it is possible that they were incapable of comprehending the probabilities attached to the game and the likelihood of an event. However, the surveyor asked them questions, such as "how much do you get if the coin lands on tails? And on heads?" to ensure that the child understood the game. Additionally, I control for the quantitative ability, as reflected in the math scores, in my regressions.

VI. SUMMARY STATISTICS

A) *Summary of Risk Game Results*

The distribution of the lottery choices, as can be seen from table 6.1, is skewed to the left. This is slightly interesting as for most lottery games, as in Binswanger (1980), the distribution is flattened at the ends. In my sample, almost 50% of the children are in "slight to neutral" and "neutral to negative" classes, that is they are risk loving. This reiterates the concern that the children were incapable of gauging the risk involved in the various lottery choices. In light of such a distribution, the case for controlling for cognitive ability becomes all the more compelling.

Table 6.1 Risk Game Results

Gamble Choice	Payoff Low	Payoff High	Expected payoff	Variance	Risk Aversion Class	Frequency (%)
1	50	50	50	0	Extreme	9.98
2	40	100	70	900	Severe	10.88
3	30	130	80	2500	Intermediate	13.56
4	20	160	90	4900	Moderate	17.66
5	10	190	100	8100	Slight to neutral	23.75
6	0	200	100	10000	Neutral to negative	24.17

B) *Summary of the descriptive statistics*

Table 6.2 reports the descriptive statistics of the independent variables. The independent variables can be divided into four broad categories,

- Economic Factors – These comprise of the wealth index (*wi*), enrolment in a public school (*public*), and drought variables. Wealth index is composite of consumer durables owned by the household, the quality of house residing in and the access to services such as electricity, water and toilet facilities. Attending a public school is conditioned on the household income, school fees and provision of mid-day meals at school, and thus an economic decision. It also reflects the investment by the household in children. There are two variables to study the impact of a drought. *Drought* is the dummy for the household suffering from a recent drought (2006-09). *Susdrought* is a dummy for households which suffered from repeated droughts (2 or more) from 2002-09. Overall, there is a positive correlation between wealth index and the riskiness of the lottery choice. This strengthens my initial hypothesis that children born into an economically disadvantaged environment suffer an "accident" and lag behind the "luckier" counterparts in terms of skill formation. No conclusive inference can be made from the means of the drought variables over the risk categories. Low mean value for *drought* dummy is perhaps, because there were no significant droughts experienced by the region during 2006-09.

Table 6.2 Descriptive Statistics

	Lottery Choice					
	Least Risky	→	→	→	→	Most risky
Explanatory Variables	1	2	3	4	5	6
Economic Factors						
Wealth Index (*wi*)	0.49	0.49	0.47	0.51	0.55	0.55
	(0.19)	(0.19)	(0.18)	(0.19)	(0.17)	(0.18)
Attends Public school (*Public=1*)	0.61	0.57	0.66	0.56	0.5	0.55
	(0.5)	(0.5)	(0.48)	(0.5)	(0.51)	(0.5)
Drought 2006-09 (*drought=1*)	0.09	0.09	0.08	0.06	0.07	0.08
	(0.28)	(0.28)	(0.27)	(0.24)	(0.25)	(0.27)
Repeated drought shocks (*susdrought=1*)	0.06	0.06	0.05	0.04	0.04	0.04
	(0.24)	(0.23)	(0.22)	(0.18)	(0.2)	(0.19)
Psychological Factors						
Father *(=1*)	0.8	0.84	0.87	0.84	0.85	0.87
	(0.41)	(0.38)	(0.35)	(0.38)	(0.36)	(0.35)
Social Inclusion (*game=1)*	0.77	0.64	0.75	0.8	0.81	0.8
	(0.43)	(0.49)	(0.44)	(0.41)	(0.4)	(0.41)
Death of hh member - 2006-09 (*deathany=1*)	0.12	0.08	0.09	0.07	0.09	0.06
	(0.32)	(0.26)	(0.28)	(0.25)	(0.28)	(0.23)
Individual level controls						
Math Scores (*math_co*)	9.91	9.26	9.3	10.43	10.47	11.27
	(5.37)	(5.65)	(5.2)	(5.23)	(5.16)	(5.31)
Female *(=1*)	0.51	0.5	0.51	0.47	0.43	0.46
	(0.51)	(0.51)	(0.51)	(0.5)	(0.5)	(0.5)
N*(Total=1904)	190	207	258	336	452	460
NREGS						
Work under NREGS (*nrwork=1*)	.71	.65	.77	.77	.73	.81
	(.45)	(.48)	(.42)	(.42)	(.44)	(.39)
N**(Total=1404)	146	160	204	243	330	321

The mean and standard errors have been reported by risk category. Standard errors are in parenthesis.

*Number of observations. **Number of observations given sample is restricted to rural.

- Psychological Factors – These include dummies for being included in the game with peers (*game*), meeting father daily (*father*) and if the household suffered a loss of the family member in recent past *(deathany*). On the whole, the mean for the variables, *father* and *game*, increases with the riskiness of the lottery choice, pointing at the importance of emotional experiences in shaping risk attitudes.
- Individual controls – Math scores (*math_co)* controls for the mathematic ability of the child in comprehending the likelihood of winning an amount in the different lottery choices. *Female* dummy controls for the gender. Empirical literature seems to suggest that females on an average are more risk averse than males. A similar trend is noticeable from the summary statistics – a lower number of females opt for the riskiest lottery choice. Since the children in my sample are very young, it interesting to see that the distinction between male and female has already set in. Dohmen *et al* (2007) find that risk aversion is correlated with cognitive ability. In my study too, as is clear from the descriptive statistic, children with higher mean math scores opt for riskier options.
- Role of NREGS – To study the impact of social protection program, NREGS, I use the variable *nrwork* which takes the value of *1* if the household found work under the NREGS. The mean value for each risk category is high, implying a high degree of participation in the program. Also, noticeable is a higher mean value for the riskiest category *vis-à-vis* the least risky category.

VII. EMPIRICAL STRATEGY

A) Background

Risk aversion is generally understood and modelled with respect to the von Neumann-Morgensten Expected Utility Function. There are three commonly used measures of risk aversion.

1. Absolute Risk Aversion (Pratt, 1964; Arrow, 1965): A(W) = $-\frac{U''(W)}{U'(W)}$
2. Relative Risk Aversion (Arrow, 1965, 1971): R(W) = $-\frac{WU''(W)}{U'(W)}$
3. Partial Relative Risk Aversion (Hanson & Menezes, 1970): $P(W_0;m) = -\frac{mU''(W_0+m)}{U'(W_0+m)}$

Where W is the total wealth, W_0 is the initial wealth and m is the monetary gain or loss. U' and U'' are the first and second order derivatives of the Expected Utility function.

The relationship between absolute risk aversion, relative risk aversion and partial relative risk aversion can be described as follows:

$$R(W) = W_0 A(W) + P(W_0; m)$$

The importance of A(W) arises when an individual's risk aversion behaviour is considered as wealth is varied keeping the risk unchanged. R(W) becomes relevant when both wealth and risk change in the same proportion. $P(W_0;m)$ is important in scenarios when wealth is fixed but the risk is varied. I shall be using the Constant Partial Relative Risk Aversion measure (CPRA) for my analysis as used by Binswanger (1980) and Barr & Genicot (2008) in their analysis while working with Binswanger type lotteries. Since the wealth remains unchanged during the experimental study and the expected payoff m varies over the lottery choices, CPRA is a natural choice for my analysis. Hereafter, the risk aversion measure that I use in this paper is CPRA.

B) Risk Aversion measure – Dependent Variable

I contruct two measures of risk aversion from the data. First, I construct a measure of risk aversion by estimating the bounds for risk aversion parameter for each individual assuming CPRA utility under the EUT framework (see table 7.1). The bounds are arrived at by equating the CPRA utility of the successive gamble choices. The CPRA utility function is given as,

$$U(x) = (1 - r)x^{1-r}$$

Where x is the lottery prize and r is the risk aversion measure I wish to estimate. If r=0, the individual is risk neutral; if r>0, the individual is risk averse; if r<0, the individual is risk seeking.

I use the log of the geometric mean of the lower and upper bounds of this measure as my dependent variable. For the "slight to neutral" and the "neutral to negative" classes, the lower bounds are 0 and $-\infty$. Hence, some scaling is required. Following the Binswanger paper (1980), I have taken the aritmetic mean of the lower and upper bounds for “slight to neutral” class and set the lower bound for the “neutral to negative” class to an arbitrary small number (0.0007). I then run an OLS regression on this continuous measure. To interpret the effect of explanatory variables on this measure, a negative coefficient would imply a decrease in risk aversion and vice versa

Table 7.1 CPRA Risk Aversion Measure

Gamble Choice	Payoff Low	Payoff High	Expected payoff	Variance	Risk Aversion Class	Partial Relative Risk Aversion Bounds
1	50	50	50	0	Extreme	infinity to 7.51
2	40	100	70	900	Severe	7.51 to 1.74
3	30	130	80	2500	Intermediate	1.74 to .812
4	20	160	90	4900	Moderate	.812 to .316
5	10	190	100	8100	Slight to neutral	.316 to 0.00
6	0	200	100	10000	Neutral to negative	0 to -infinity

The second measure is calculated by making use of the ordinal choice of lottery. Children who selected lottery choice 5 and 6 are categorised as “risk loving” and the rest as “not risk loving”. My dependent variable now changes to “risk loving”. I then run a probit on this dicrete measure which takes the value of 1 for “risk loving” children and 0 for “not risk loving” children. A negative coefficient, in this case would imply a decrease in the probability of showing “risk loving” attitude.

C) Econometric Model – Childhood determinants of risk aversion

First, I study the determinants of childhood risk aversion using a sample of 1950 children. Using my first measure of risk aversion (CPRA), I estimate an OLS regression:

$$y_i = \beta_0 + \beta_1 E_i + \beta_2 P_i + \beta_3 X_i + u_i$$

Where E_i includes wealth index, a dummy for whether the child attends public school and a shock component – if the household suffered from drought. P_i includes the variables whether the child interacts with his father regularly, whether he/she is included in the games played by his/her peers and a shock component – if he has suffered loss of a family member. X_i controls for the gender and math ability of the child. Standard errors are made robust to correct for any heteroskedasticity that may arise due to correlation between unobservables and the dependent variable. They are also clustered at the sub-district level (21 *mandals*) to correct for district fixed effects – children belonging to a certain *mandal* may be affected by the same heterogeneity of unobservables (law and order, political stability) resulting is similar variance within *mandals*.

Using the second measure, I set up a probit model. The dependent variable is "risk loving". Although I could have used a logit model, empirically it makes little difference (Cameron &Trivedi, 2006). Building on the probit model, the dependent variable, y, takes the value of 1 if the child is "risk loving" and 0 if he is not. Thus,

$$P(y_i = 1|z) = P(y_i = 1|\beta_0 + \beta_1 E_i + \beta_2 P_i + \beta_3 X_i) = \Phi(\boldsymbol{z\beta})$$

$\Phi(\boldsymbol{z\beta})$ is a standard normal cumulative distribution function. This is a non-linear model which I estimate using log-likelihood function. The estimators one gets from Maximum Likelihood function are consistent, asymptotically efficient and asymptotically normal. However, this is conditioned on the fact that the model has been correctly satisfied. Non-normality or heteroskedasticity of the error term might lead to inconsistent estimators. I report the Wald test in the results section to examine for possible misspecification of the model.

D) Econometric Model – Role of NREGS

The second part of my analysis is to study the effectiveness of NREGS in helping households to cope with shocks and smooth income, resulting in less risk averse children. Since the scheme was available to only rural households, I restrict my sample to rural areas. 73.8% of the sample households reside in rural regions and are thus, eligible for the scheme. Restricting my study to the rural areas, would mean that I am incapable of making a policy advice of extending the NREGS program to the public in general due to its success in rural households in smoothing income. However, that is not the point of this analysis. My analysis is restricted to study the effectiveness of the program among the people who had access to it.

The most important concern in dealing with the effectiveness of NREGS is one of self-selection, and it is the most challenging to deal with. Self-selection bias occurs in my analysis because participation in the NREGS is not random. This bias is due to two factors. First, the NREGS was implemented in a targeted fashion, targeting the most backward districts first. To correct for this, I cluster the standard errors at the district level. Household living in a certain district which received the NREGS prior to other districts, might behave in a similar fashion different from households in other districts. Second, household were free to register for the program. This introduces self-selection into the program. I deal with this issue by looking at whether the household secured work under the scheme rather than whether it has a job card under the scheme. Once the household registers for the program, it has created a demand for employment. However, getting a job under the scheme is a supply side phenomenon which is arguably exogenous to my model. Additionally, I estimate the average treatment effect of participation in the NREGS by estimating propensity score. The method implemented for Propensity Score Matching (PSM) is described below.

The matching approach is one possible solution to the selection problem. The basic idea is to match the non-participants with the participants who are similar terms of observable characteristics X. However, since conditioning on all relevant covariates would result in a high dimension of X, Rosenbaum and Rubin (1983) suggested the use of balancing scores. One such balancing score is the propensity score which measures the probability of participating in a program given the observable characteristics, X.

$$P(X) = P(D = 1|X)$$

Where P(X) is the propensity score and D is the dummy for having received the treatment, that is, of being covered by the NREGS. For the binary treatment case, where probability of participation versus non-participation is to estimated, logit and probit models usually yield similar results (Caliendo & Kopeinig, 2005). Hence, the choice is not too critical, even though the logit distribution has more density mass in the bounds. I use the logit model to estimate the propensity score. In my estimation, I use the observable characteristics which would affect both participation in NREGS and the risk aversion in children from Young Lives Round 2 data (2006-07).

Once the propensity score has been obtained, I carry out matching using two methods – 5-Nearest Neighbour and Kernel Density. I use the optimal bandwidth value (0.044) as suggested by Silverman (1984) to carry out Epanechnikov kernel density matching. The impact of the program or the average treatment effect on the treated is given as,

$$ATT = \frac{1}{T}\sum_{i=1}^{T}(Y_{i1} - \sum_{j=1}^{C} W_{ij}Y_{j0})$$

Where Y_{i1} is the measure of risk aversion in children belonging to participating (treated) households, Y_{j0} is the measure of risk aversion in children belonging to non-participating (control) households, T and C denote the treated and control groups respectively, and W_{ij} denotes the weights assigned to the control group matches - kernel-weights which give higher weights to the closer matches of non-participants and 5-nearest neighbour provide uniform weights. Using only 1 nearest neighbour may produce bad matches as high score participants may be matched with low score participants. This concern is subsumed by allowing for matching with replacement and multiple neighbours. Furthermore, kernel density matching is used which uses more information and relies on non-parametric matching.

VIII. RESULTS

A) Childhood Determinants of Risk Aversion

Table 8.1 reports the results of regressions for both OLS and probit models. Additionally, the Wald test has also been reported for the probit model. The null hypothesis under the Wald test is that the variables of interest are all insignificant. The small p-value reported in my results rejects the null. Also, one can note that the predicted value for being "risk loving" under both probit specifications is very close to the actual value.

Columns 1 (OLS) and 2 (probit) of table 8.1 report results of regressions with shocks from the recent past - death of a household member and drought. Although death of a household member makes the child more risk averse (significant coefficient at 5% level of significance under OLS), the effect is not strong enough to push him out of "risk loving" category (insignificance under probit). This is to say that the child who has suffered a loss would still be willing to take risks but not to the same extent as those who haven't been subjected to same personal grief. The insignificant effect of an economic shock as captured by the variable, drought seems to indicate that psychological trauma loom larger in shaping the personality of the child than economic uncertainties.

Columns 3 (OLS) and 4 (probit) of table 8.1 report results of regressions with sustained economic shock – households which suffered from repeated droughts since 2003. This exercise was undertaken to see if children who have been exposed to repeated shocks develop more risk averse behaviour. An insignificant coefficient seems to reiterate the fact that children in their early years are not profoundly affected by the economic shocks.

Table 8.1 Regression Results

	(1) lncpra	(2) risklov	(3) lncpra	(4) risklov
Wealth Index (*wi*)	-2.592***	1.269***	- 2.556***	1.256***
	(0.175)	(0.0734)	(0.184)	(0.0738)
Attends public school (*public=1*)	-0.356***	0.102	-0.359*	0.101
	(0.505)	(0.280)	(0.584)	(0.287)
Father *(=1)*	-0.0986	0.0212	-0.147	0.0322
	(0.203)	(0.0829)	(0.191)	(0.0825)
Social Inclusion (*game=1*)	-0.319*	0.153**	-0.319**	0.155**
	(0.176)	(0.0676)	(0.145)	(0.0674)
Female (*=1*)	0.241	-0.126**	0.248*	-0.127**
	(0.149)	(0.0607)	(0.131)	(0.0601)
Math scores (*math_co*)	0.0446***	0.0109	0.0462**	0.0112
	(0.0149)	(0.00703)	(0.0177)	(0.00697)
Death of hh member-2006-09 (*deathany=1*)	0.538**	-0.0912		
	(0.268)	(0.111)		
Drought-2006-09 (*drought=1*)	0.00636	-0.00646		
	(0.311)	(0.126)		
Repeated drought (*susdrought=1)*			0.36	-0.0690
			(0.358)	(0.217)
Constant	0.236	-0.948***	0.297	-0.959***
	(0.361)	(0.147)	(0.326)	(0.153)
Observations	1,895	1,893	1,893	1,893
Predicted Pr(risklov)		0.478		0.478
Observed Pr(risklov)		0.4792		0.4792
Wald Test (p-value)		0.000		0.000
F-statistic	8.64		11.19	
R-squared	0.0325		0.031	

Robust standard errors are given in parenthesis. ***p<0.01, **p<0.05, *p<0.1

Children who attended public school are less risk averse than those attending private school (significant coefficients in columns 1 and 3). This can be explained through the Mid-Day Meal Scheme (MDMS) operational in India. Public schools provide meals to the children. Hence, children attending public school, did not suffer from a drop in nutritional intake due to economic shocks. Singh, Park and Dercon (2012) report significant gains in health for Indian children covered by the MDMS in the face of a drought. Following from this, public schools serve as a cushion from adverse shocks resulting in a more stable and safer environment for children. This safety net might explain the lower risk aversion that my regression analysis captures.

A very important result from this study is the significance (p-value < 0.01) of the wealth index in reducing risk aversion. This upholds Heckman's claim that the environment of birth plays a significant role in developing skills. Children who were born into households with access to basic amenities, good housing and high level of ownership of consumer durables, exhibit not only lower degree of risk aversion, but are "risk loving". A 1% point increase in the wealth index increases the probability of being "risk loving" by 0.5% points (table 8.2).

Table 8.2 Marginal Effects of the Probit Models at the Means

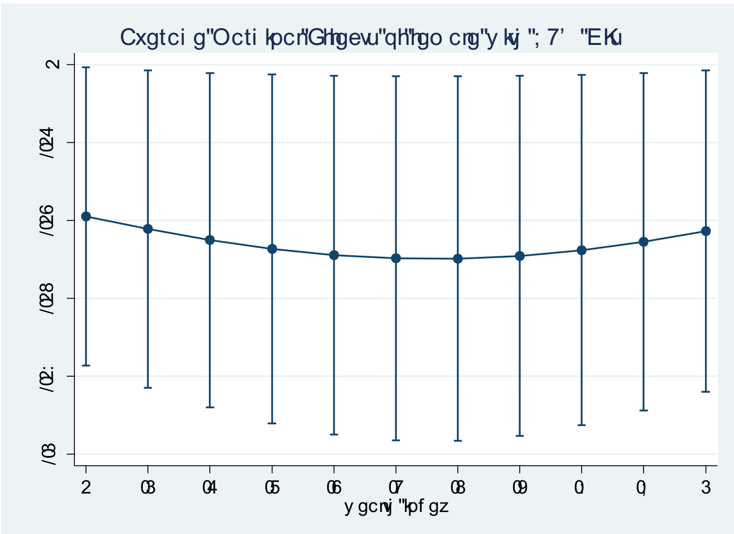
	dy/dx			
	(2)		(4)	
Wealth Index (*wi*)	0.505***	(.112)	0.5***	(.115)
Attends public school (*public=1*)$^{+}$	0.041	(.029)	0.04	(.029)
Father (*=1*)$^{+}$	0.008	(.033)	0.013	(.033)
Social Inclusion (*game=1*)$^{+}$	0.061**	(.027)	0.061**	(.026)
Female (*=1*)$^{+}$	-0.05**	(.024)	-0.05**	(.024)
Math scores (*math_co*)	0.004	(.003)	0.004	(.003)
Death of hh member-2006-09 (*deathany=1*)$^{+}$	-0.036	(.044)		
Drought-2006-09 (*drought=1*)$^{+}$	-0.003	(.05)		
Repeated drought (*susdrought=1*)$^{+}$			-0.027	(.086)

($^{+}$) dy/dx is for discrete change in dummy variable from 0 to 1. ***p<0.01, **p<0.05, *p<0.1 Standard errors are reported in the parenthesis.

Reiterating the importance of psychological factors *vis-à-vis* economic ones is the significant coefficient for social inclusion variable. Children, who feel socially accepted, are less risk averse. Being included in their peer group increases their probability of exhibiting "risk loving" behaviour by .06% points (table8.2).

Interesting to note is the difference between males and females in their risk taking attitude. Females are more risk averse than males. The CPRA risk aversion measure is 24.8% higher for females implying a higher degree of risk aversion. Also, as reported in table 8.2, the probability of choosing the riskiest bet reduces by 0.05% points in the case of females. Figure 8.3 plots the marginal effect of the difference between males and females on the probability of being "risk loving" as the wealth index increases. As we can see, at all levels of wealth index, females are more risk averse. However, interesting to note is that at very high and very low levels of wealth index, the marginal effect of being a female on risk attitude is the same. This seems to suggest that at the extremes, economic standing plays a more dominant role in predicting risk attitudes. This strengthens Heckman's argument for an early childhood investment to correct for the "accident" of birth into an economically poor household.

Figure 8.3 Average Marginal Effects of Female on Predicted Probability



B) *Role of NREGS*

Table 8.4 reports the results of the logit regression to estimate the propensity score. The sample has been restricted only to rural household (1404 observations) in this section, since only rural households had access to the scheme. The mean propensity score is 0.682 (with a standard deviation of 0.225) which is comparable to the mean score from the sample (0.683 with a standard deviation of 0.465).

Table 8.4 Logit Regression of participation in NREGS

Covariates	Estimate	Std. Err.
Scheduled Caste	0.945***	(0.241)
Scheduled Tribe	0.755***	(0.260)
Other Backward Class	0.404**	(0.204)
Parent's Education (Average Years)	-0.056***	(0.021)
Salaried Employee	-0.119	(0.173)
Main Source of Income : Agriculture	0.888***	(0.138)
Hindu	2.233	(0.905)
Muslim	1.921	(0.996)
Income from Pension	-0.258	(0.397)
Income from Social Security (other than NREGS)	-0.239	(0.175)
Participation in Indira Kranthi Patham (IKP)	-0.105	(0.230)
Easily Raise Rs. 1000	-0.344**	(0.138)
Suffered Increase in Input Prices	0.152	(0.243)
Suffered Drought	0.229	(0.148)
Suffered Crop Failure	0.296	(0.185)
Suffered Livestock Death	0.094	(0.254)
Housing Services Index	-2.796***	(0.473)
Consumer Durables Index	-1.141**	(0.468)
Intercept	-0.220	0.960

***p<0.01 **p<0.5 *p<0.1. Standard errors are reported in parentheses. The dependent variable is the binomial indicator whether a household participated in the NREGS (1 = participation).

The results of the propensity score estimation are in accordance with the economic literature and research undertaken to study the impact of the NREGS. Uppal (2009) noted that belonging to Scheduled Caste and Other Backward Class, as well as being engaged in agriculture increase the probability of participation into the program. Similar results hold for my analysis. Belonging to a socio-economically deprived section of the society has a strong positive impact on participation. Also, housing services index and consumer durables index, a good proxy for the economic standing of the household, are negatively correlated with program participation. This seems to suggest that the self-targeting mechanism of the scheme works well with the disadvantaged communities enrolling into the program. Being engaged in agriculture may leave the people seasonally unemployed, thereby increasing the chances of such people participating in the program. This is in unison with the findings of Ravi and Engler (2009). An interesting variable is the ease with which household can raise Rs.1000 reflecting the liquidity constraint. Households which can easily raise Rs. 1000 are less liquidity constrained and are less likely to register for NREGS.

Table 8.5 reports the estimates of the average effect on risk aversion in children due to participation in NREGS. Using the 5-nearest neighbour estimate, I find a significant (p-value<0.1) effect on risk aversion due to enrolment in NREGS – it reduces the CPRA risk aversion measure by 42.9% implying lower risk aversion. In the nearest neighbour method, all treated units find a match. However, it is obvious that some of these matches are fairly poor because for some treated units the nearest neighbour may have a very different propensity score (Becker & Ichino, 2002). With kernel matching, all treated are matched with weights that are inversely proportional to the distance between the propensity scores of treated and controls. The estimated ATT using kernel matching and optimal bandwidth formula (Silverman, 1984) shows that participation in NREGS reduces risk aversion by 35.6% among children.

Table 8.5 Average Treatment Effect on the Treated

Method	ATT	Std. Error	p-value
5-Nearest-Neighbour	-.429*	.2543	0.092
Kernel Density	-.3569*	.2029	0.079

ATT – Average Treatment Effect on the treated. Bootstrapped Standard Errors with 200 repetitions. Controls in place are attends public school, female, math scores, social inclusion, meeting father regularly. These controls affect risk aversion in children, but not the participation into NREGS. * Significant at 10%

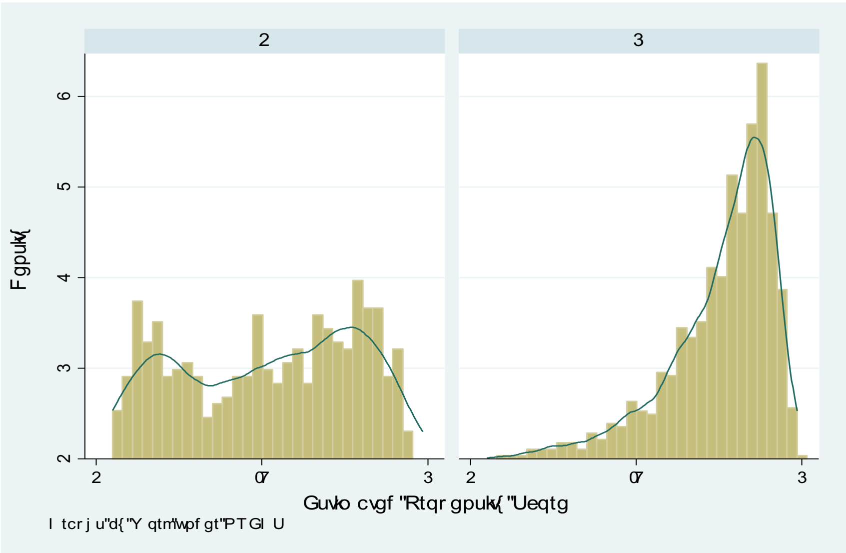
C) Robustness Check

As mentioned earlier in Section III, there are a host of factors that may affect risk attitudes but are not captured in the model. This, I address by controlling extensively for observed individual and household characteristics. However, one cannot overlook the possibility of unobservables influencing risk behaviour.The downside of including many independent variables is that this may lead to the problem of multicollinearity. Multicollinearity inflates the standard errors and results in statistically insignificant coefficients interfering with inference and hypothesis testing. I test for any co-linearity by looking at the OLS regression and variance of influence (VIF) analysis and find that the VIF is less than 2 for each variable. A common rule of thumb is that if $\text{VIF}(\widehat{\beta_\iota}) > 10$, multicollinearity is high. Hence, for my results, multicollinearity is not a cause of worry.

Second, 24% of the children in my sample choose the riskiest lottery choice (Gamble choice 6), although it represents the same expected payoff as the less risky lottery choice 5. This may not be considered rational behaviour. I conduct a robustness check, by excluding the respondents (460 observations) who chose the riskiest option and estimating the OLS and probit models on the reduced sample. The results showed that there is no difference in the sign or statistical significance of the coefficients. Hence, I can safely conclude that the results reported in my study are not driven by the respondents opting for the "inefficient" choice 6.

Third, PSM relies on two assumptions – conditional independence assumption (CIA) and overlap assumption. According to CIA, the potential outcome is independent of the treatment assignment given the vector of observable characteristics. This is commonly known as the "unconfoundedness" or "selection on observables" assumption. In addition to this, is required the overlap condition which ensures that for each treated unit, there is a control unit with the same observables. Rosenbaum and Rubin (1983) defined the treatment as strongly ignorable when both unconfoundedness and overlap conditions are valid. Given these, one can identify the ATT. The most straightforward way to check for the overlap condition is to analyse the density distribution of the propensity score in both, treated and control groups. It can be seen from Figure 8.6 that there is there is considerable overlap of estimated propensity scores between the treated (right graph) and untreated (left graph) groups. For propensity scores close to 1, there are no control individuals. Hence, the propensity score estimation has been restricted to region of common support. This improves the quality of matches in estimating the ATT. However Lechner (2001) observed that in this way, high quality matches may be lost at the boundaries of the common support and the sample size may be reduced. Imposing a common support condition in my analysis reduces the sample size to 1379 from 1404 which does not pose any serious threat to the robustness of my analysis, as noted by Bryson, Dorsett, and Purdon (2002).

Figure 8.6 Histogram of propensity score for control and treatment groups



To check for the validity of the CIA assumption, I have implemented a sensitivity analysis as proposed by Ichino, Mealli, and Nannicini (2008(Arrow 1971)). This test allows for the possibility of violation of the CIA. A binary variable which can be simulated and which acts as a potential confounder is used as an additional covariate in combination with the preferred matching estimator. A comparison of the estimates obtained with and without matching on the simulated confounder shows the extent to which the estimated ATT differs. Since the NREGS was implemented in a phased manner, I use a confounder dummy variable which takes a value of 1 if the households were covered by NREGS in Phase 1 (2005-06), and a value of 0 if they were covered in the subsequent period. The argument is that the districts which were exposed to the coverage of NREGS for a longer time period might have well developed institutions in place for implementation of NREGS and development of worksites. This could possibly encourage households to participate in the program. I allow the confounder to mimic the distribution of this constructed binary variable and find that my results are robust to possible deviations from the CIA. Table 8.7 reports the simulated ATT.

Table 8.7 ATT Estimation with Simulated Confounder

Method	ATT	Std. Error	Outcome Effect	Selection Effect
Nearest Neighbour	-0.489	0.288	0.864	1.093
Kernel Density	-0.314	-	0.871	1.100

Both outcome and selection effect are odd ratios from logit estimations.

For the kernel density matching method, the simulated ATT is lower than that reported in table 8.5. However, the deviation from baseline results is only 12%. Additionally, the outcome and selection effects are also low. The nearest neighbour simulation is conducted for only 1 nearest neighbour matching, and hence I cannot compare these to the baseline results. This robustness check should be treated with caution – I cannot conclusively rule out the possibility of "selection on unobservables" and that might produce biased (upward bias) coefficient estimates for the ATT.

Lastly, in order to ensure the matching quality, one has to check that the distribution of the covariates is balanced in both the control and treatment groups. There should be no significant difference in the mean of the estimated propensity score between the treatment and control group. This implies that additional conditioning on the observables should not provide new information about the treatment decision. Table 8.8 reports the results of the two tests used to assess the matching quality – Standardised bias test, and the t-Test. Standardised bias suggested by Rosenbaum and Rubin (1985) is defined as the difference of the means between the treated and matched control subsamples as a percentage of the square root of the average of sample variances in both groups.

Table 8.8 reports the % bias after matching. Although there is no clear rule for success of matching, most empirical studies coinsider a bias of less than 5% as sufficient. Following this, I find sample is balanced for almost all covariates under both, kernel density and 5-nearest neighbour approach. The variables which register a % bias of more than 5% register a very small t-statistic, and thus a high p-value. This implies that one cannot reject the null of insignificant difference in the means between the treated and control groups.

Table 8.8 Assessing Matching Quality

	Kernel Density			5 Nearest Neighbour		
Variable	%bias	t	p>t	%bias	t	p>t
Scheduled Caste	3.9	0.78	0.435	3	0.61	0.544
Scheduled Tribe	1.6	0.32	0.750	1	0.19	0.851
Other Backward Class	-5.8	-1.24	0.214	-4.6	-1.00	0.320

Parent's Education (Average Years)	3.5	0.91	0.364	5.5	1.45	0.146
Salaried Employee	-1.2	-0.28	0.779	0.5	0.13	0.896
Main Source of Income : Agriculture	6.9	1.48	0.138	6.8	1.47	0.141
Hindu	-1.8	-0.58	0.562	-2.1	-0.71	0.481
Muslim	1.8	0.55	0.581	2.2	0.67	0.500
Income from Pension	1.7	0.40	0.686	1.3	0.31	0.755
Income from Social Security (other than NREGS)	-7.8	-1.62	0.104	-3.5	-0.75	0.454
Participation in Indira Kranthi Patham (IKP)	1	0.21	0.830	3.8	0.85	0.393
Easily Raise Rs. 1000	-6.3	-1.34	0.180	-6.7	-1.42	0.155
Suffered Increase in Input Prices	0.7	0.15	0.881	0.6	0.13	0.899
Suffered Drought	-4.7	-0.96	0.336	-2.8	-0.59	0.557
Suffered Crop Failure	-1	-0.21	0.834	1.6	0.33	0.741
Suffered Livestock Death	-1.5	-0.31	0.755	-3.7	-0.75	0.456
Housing Services Index	5.6	1.74	0.082	5.5	1.72	0.085
Consumer Durables Index	-2.1	-0.47	0.636	0.1	0.03	0.980

IX. CONCLUSION

This paper examined the determinants of childhood risk aversion and found that psychological factors, such as, death of a family member and inclusion in peer groups play an important role in shaping risk attitudes. The results also highlight the importance of socio-economic environment into which a child is born, as captured by the wealth index, in shaping risk attitudes. 58% of the children who exhibit "risk loving" tendencies come from households with an above mean wealth index (0.512).

The paper additionally studies the effectiveness of the NREGS in ensuring a safe and stable environment for children, reflected in lower risk aversion. NREGS, being a targeted program and harbouring self-selection among the eligible rural households, poses serious econometric issues when studying the impact. However, this is overcome by using a rich Young Lives panel data. Round 2 data with exhaustive information on household level characteristic is used to conduct a propensity score matching analysis. This is followed by studying the impact of the NREGS on the risk aversion behaviour in children recorded in Round 3. NREGS reduced risk aversion in children by 36-43%. The results from PSM are made robust, by conducting tests to ensure balancing, by ensuring the validity of overlap condition, and by ensuring the validity of unconfoundedness assumption through simulation model using confounder. The NREGS have a significant negative impact on the risk aversion, that is, children belonging to households covered under NREGS are able to partly correct for the "accident" of birth and show signs of lower risk aversion.

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