Can public health insurance mitigate adverse impact of health shock on children's educational outcome?

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Abstract

Can public health insurances mitigate the adverse impact of health shock on children's educational outcome? We explore this question in the context of a publicly financed health insurance scheme in the Indian states of Andhra Pradesh and Telengana. Exploiting the staggered roll out of the health insurance scheme, we employ a difference-in-difference framework to study the interaction between adverse health shock and health insurance availability. We make a distinction between health shock to a child and parental health shock and long-term outcome-grade attainment at age 15, and short-term outcome- cognitive scores. We find that the impact of health shock and the mitigating role of health insurance depends crucially on the type of the adverse health shock, age of exposure to health shock, and whether long-term or short-term outcome is being studied. Combining a household level panel from Young Lives India with administrative records, we find evidence that health insurance availability can partially mitigate the adverse effect of child health shock and parental health shock on long-term and short-term outcome respectively.We further find child health shock to have a positive impact on short term outcome, which is partially reduced by health insurance availability. In this context, we offer suggestive evidence that this phenomenon occurs through the channel of compensating parental investment.

Keywords: public health insurance, education, early life, cognition
JEL Classification:I13, I15, I21,O15

1. Introduction

It is well established that early childhood circumstances can have long term implications (Case et al., 2005). Such long term consequences can be seen in health, education, and labour market outcomes in adulthood. Poor health in childhood can have a persistent effect, leading to poor educational attainment (Currie and Hyson,1999), poor cognition (Glewwe and King,2001; Figlio et al.,2014), along with poor health status in adulthood (Palloni et al., 2009; Currie et al.,2010).However,whether the effects of such adverse childhood circumstances can be mitigated through subsequent investments or policy interventions remains an open question, with some studies arguing that mitigation is not possible (Victora et al., 2008), while other studies argue for the possibility of mitigation (Crookston et al., 2010). We explore this question in the context of a publicly financed health insurance program in the Indian states of Andhra Pradesh and Telengana. In particular, we ask the following question: can public health insurance mitigate adverse impact of health shock on children's educational outcome?

We answer this question by exploiting the staggered roll out of a publicly financed health insurance scheme Rajiv Aarogyasri (RAS), currently known as Dr. YSR Aarogyasri in Andhra Pradesh and Aarogyasri in Telengana. For the sake of clarity, we would refer to the scheme as Rajiv Aarogyasri as being applicable to both Andhra Pradesh and Telengana. We combine child data from Young Lives India with administrative data on program roll out to construct our RAS exposure variable. The Young Lives tracks two cohorts of children: Old Cohort (OC) born in 1994-95 and Young Cohort (YC) born in 2001-02. The staggered roll out of RAS generates variation in months of exposure to health insurance by year and district of residence. We make a distinction between health shock to child and health shock to parents in our analysis due to the plausibly distinct channels through which the health shock would operate. Health shock to parents can lead to a loss of income or increase in medical expenses,which can affect the child's educational outcome (Dhanaraj,2015,2016; Alam,2015; Bratti & Mendola,2014). On the other hand, health shock to child can impact the child's health status and thereby affect educational outcome. It can also affect educational outcome through an increase in household expenses. We measure educational attainment through two indicators: standardized Peabody Picture Vocabulary Test (PPVT) scores, and grade attainment at age 15. Experience of parental health shock is not found to have any long term impact on grade attainment. On the other hand, we find that experience of health shock by the child during the age 5-8 reduces grade attainment at age 15, while exposure to RAS is found to partially correct for this negative impact. Experience of health shock later in childhood is not found to have any impact on grade attainment at age 15. The finding suggests that the timing of the shock and the intervention is crucial factor in determining the impact on educational outcome. Contrary to grade attainment, parental health shock is found to have negative impact on standardized PPVT score, which is partially corrected by RAS exposure. This finding suggests parental health shock has only a transitory effect on a child's educational outcome. In contrast to parental health shock, experience of health shock by the child is found to improve standardized PPVT score, which is partially reduced by exposure to RAS. In this context we explore the underlying mechanism and find suggestive evidence that a favourable impact of own health shock on cognition is driven by compensating parental investment on education and health of the shock affected child.

This paper is related to and contributes to the existing literature in several ways. **First**, it relates to the literature exploring effects of early life circumstances. One of the prominent strands of literature,expanding on the fetal origins hypothesis, discuss how conditions *in utero* can have long term impact on adult health and thereby on cognitive and labour market outcomes (Almond and Currie,2011; Almond et al., 2018).However, apart from *in utero* conditions, conditions after birth has also been found to have long term impact. One crucial factor is health after birth, often measured through birth weight (Currie & Vogl,2003; Currie et al., 2010; Smith,2009). Apart from health at birth, health shocks after birth during childhood are also found to have lasting impacts on physical health, mental health, and cognitive outcomes (Currie et al.,2010; Gensowski et al.,2019). This is particularly relevant for developing countries where children are more susceptible to such shocks and are more likely to face multiple adverse health shocks (Currie & Vogl,2003) However, not only own health shock, children's educational, behavioural, and labour market outcomes are also impacted by parental health shocks (Morefield et al.,2011; Mendolia et al.,2019). Apart from health shocks, the literature has also discussed lasting impacts of weather shocks and social safety net programs (Shah & Steinberg,2017; Rosales-Rueda,2018; Maccini & Yang,2009; Miller & Wherry,2019; Bleakely,2010; Driessen et al.,2015). **Second**, our paper contributes to the literature on role of policy interventions in mitigating adverse shocks experienced in childhood. A sizable literature has explored the role of conditional cash transfers (CCT) in mitigating adverse consequences of early childhood circumstances by exploiting two sources of exogenous variation: a weather shock and introduction of CCT at some later period. The evidence regarding CCT in this context has been mixed. De Janvry et al. (2006), Adhvaryu et al. (2015,2018) and Duque et al. (2018) find evidence that CCTs are able to mitigate most of the adverse consequences of early life disadvantage on outcomes such as school enrolment, employment, grade attainment. On the other hand, literature has also found evidence that CCTs might not be able to correct for consequences of early life adverse shocks on other outcomes such as child labour, cognitive development, and physical health (De Janvry et al., 2006; Aguilar & Vicarelli,2011). Apart from the specific case of CCTs, other social safety net programs are also found to partially mitigate the adverse consequences of early childhood shocks (Gunnsteinsson et al,2014; Berhane et al., 2019; Dasgupta, 2017; Woode,2017). **Third**, this paper relates to the literature on parental investments. Parental investment in their children's human capital development can reinforce (Datar et al.,2010; Rosenzweig and Zhang,2009) or compensate (Behrman et al,1982; Bharadwaj et al., 2018) existing endowment differences. Conti et al(2011) suggest that reinforcing strategy is followed for education investment and compensating strategy for health investment, if parents do not display inequality aversion. Endowment differences can be due to a shock (Halla and Zweimuller,2014) or determined at birth (Becker and Tomes,1976).

The paper is organised as follows: Section 2 discusses the background of the RAS scheme, Section 3 describes the data, and Section 4 outlines the methodology. Section 5 presents the

Table 1: Phase wise expansion

Phase wise districts						
Phase	Scheme start date	Districts				
Phase-I	1.4.2007	Mahboobnagar	Srikakulam	Anantpur		
Phase-II	5.12.2007	Rangareddy	Nalgonda	Chittoor	West Godavari	East Godavari
Phase-III	15.4.2008	Medak	Karimnagar	Prakasam	Kadapa	Nellore
Phase-IV	17.7.2008	Adilabad	Kurnool	Hyderabad	Vishakhapatnam	Vijayanagaram
Phase-V	17.7.2008	Nizamabad	Warangal	Khammam	Guntur	Krishna

source: AHCT Annual Report 2009, Bid Notification

results, Section 6 discusses plausible underlying mechanism, while Section 7 concludes.

2. Background

In this paper, we evaluate the Rajiv Aarogyasri Scheme, which provided free health insurance in erstwhile undivided Andhra Pradesh. After the bifurcation of the state in 2014 into Andhra Pradesh and Telengana, the scheme became known as Aarogyasri in Telengana and Dr. YSR Aarogyasri in Andhra Pradesh. For the sake of clarity we refer to the scheme as Rajiv Aarogyasri in both Telengana and Andhra Pradesh. The Rajiv Aarogyasri Scheme (referred to hereafter as RAS) was introduced in 2006 in erstwhile undivided Andhra Pradesh. The scheme is run by the Aarogyasri Health Care Trust, set up by the State Government, under the chairmanship of the Chief Minister, and administered by a CEO(Annual Report,2009). The RAS is operated under a public-private partnership model (Reddy & Mary,2013), where tertiary healthcare needs of the poor are covered through a network of empanelled government and private hospitals. Termed as network hospitals (NWH), these empanelled hospitals are mandated to provide cashless tertiary care and follow-up care based on an extensive list of covered therapies. During the period of our study, the scheme was targeted towards the poor, with BPL families being eligible to be enrolled in the scheme. However, since 2019, eligibility in Andhra Pradesh has been expanded to include car and landowners too (The New Indian Express,2019). Total coverage provided is of Rs. 2 lakhs per family per annum on floater basis. No deductibles or co-payments are applicable under this scheme (Scheme Manual,2013).

The scheme was launched on a pilot basis in April, 2007 in the backward districts of Mahboobnagar, Anantapur, and Srikakulam. It was expanded in a phased manner to cover all the districts of Andhra Pradesh by July,2008.This staggered expansion of RAS gives us district level variation in months of exposure to RAS. Table 1 shows the staggered roll out of RAS across districts of Andhra Pradesh.

3. Data

3.1 Young Lives India

Our primary source of data is the Young lives survey in India. Young Lives India is part of the international research project Young Lives, that looks at childhood poverty in the developing countries of Ethiopia, Peru, India, and Vietnam. Young Lives India tracks 3000 children, termed as the Young Lives (YL) child, 2000 from the Young Cohort (YC) and 1000 from Old Cohort(OC), for over a period of 15 years in the states of Andhra Pradesh and Telengana. When the survey started in 2002, the YC children were 1 year old, being born in 2001-2002 and the OC children were 8 years old, being born in 1994-1995. The Young Lives India surveys were conducted over five rounds, covering a period of 15 years between 2002 and 2016. Thus the survey tracks the YC children from infancy to mid-teens, and the OC from early childhood through adulthood. Figure 1 shows the timeline of Rajiv Aarogyasri scheme and the Young Lives India survey rounds.

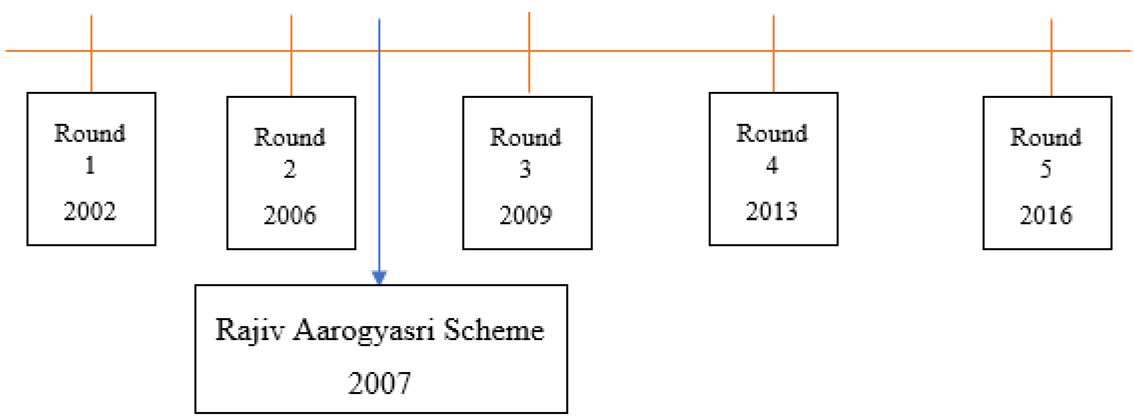

Figure 1: Timeline of Young Lives survey rounds and Rajiv Aarogyasri Scheme

The survey has collected extensive data on household level, child level, and community level characteristics of Young Lives child (referred to hereafter as YL child).Therefore, we have a rich panel data set on child characteristics, along with household and member characteristics. Data on key community level characteristics are also available.

3.2 Administrative data

Information on staggered roll out of RAS is collected from administrative reports ("YSR Aarogyasri Annual Report 2008-2009", "YSR Aarogyasri Bid notification") . These reports contain information on date of introduction of RAS, the districts where RAS was introduced, and later expanded. The details obtained from these documents, as outlined in Table 1, help us construct the exposure variable. Figure 2 shows the staggered roll out of the scheme across the districts covered in Young Lives India

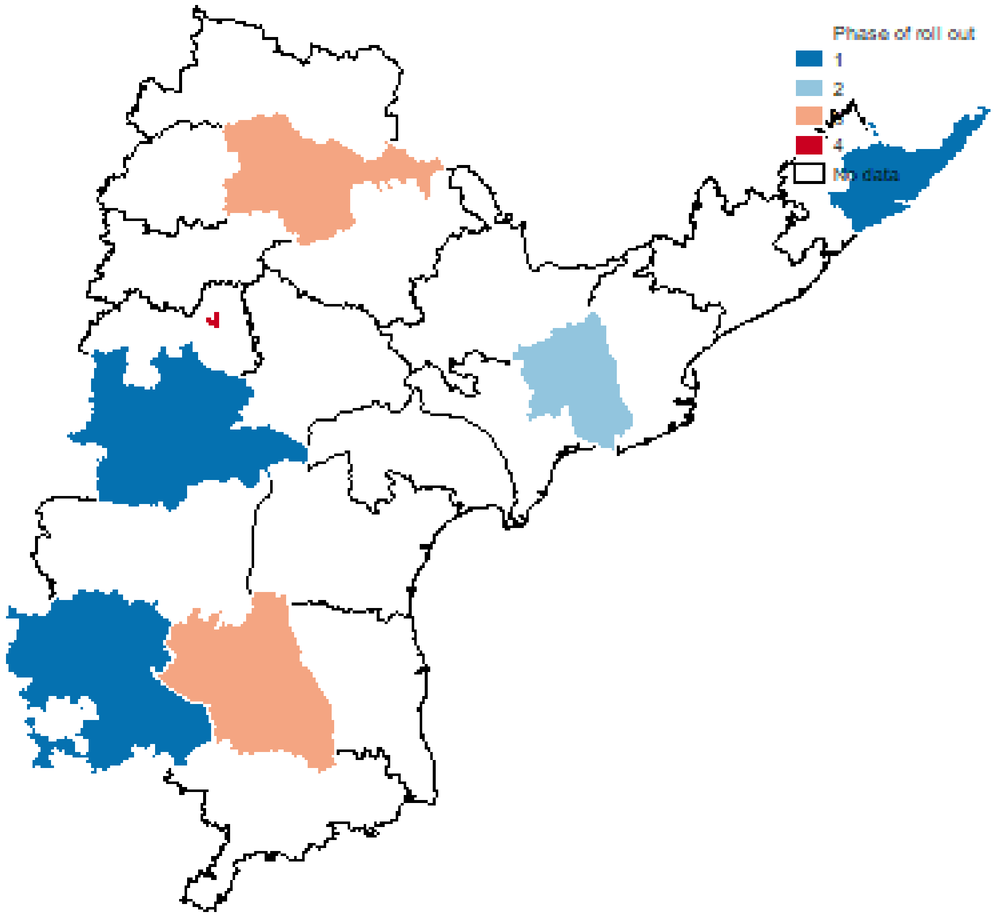

Figure 2: Staggered roll out of Aarogyasri Scheme across Young Lives districts

3.3 Aarogyasri exposure variable

Our Aarogyasri exposure variable is months of exposure to RAS. We calculate months of exposure to RAS by noting the district of residence of the household in any round. We calculate the difference in number of days between the interview date of the household and the start date of RAS in the district of residence of that household. We convert this difference to months to obtain our Aarogyasri exposure variable. Such a construction of exposure variable generates variation in exposure over time, across districts. For two households in our sample, district of residence is not consistent across rounds owing to data entry error or temporary migration or missing information. For these households, we make their district of residence consistent with that in round 3 to calculate months of exposure. Table 2 shows distribution of months of exposure to Aarogyasri scheme across survey years.

Table 2: Months of exposure

	2009-10		2013-14		2016-17	
	Mean	SD	Mean	SD	Mean	SD
Months of exposure to Aarogyasri	26.5	6.1	74.9	6.2	110.6	6.2
N	1931		1915		1900	

Table 3: Standardized PPVT score

	2007		2009-10		2013-14		2016-17	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PPVT standardized score	-.75	.94	.64	1.36	-.05	.35	.14	.35
N	1851		1901		1903		1886	

3.4 Outcome variables

Our outcome variables measure educational attainment. With this objective in mind, we look at standardized Peabody Picture Vocabulary Test (PPVT) scores and grade completion at age 15.

PPVT: We look at PPVT scores for YC children only as this variable is available consistently across all four rounds of the survey starting from round 2. In contrast, the variable is only available for two rounds in OC and due to limited sample size, we limit our analysis of PPVT scores to YC. While the data contain raw PPVT scores, we standardize the raw scores over all periods in accordance with Attanasio et al.(2020). Table 3 shows distribution of standardized PPVT scores across survey years.

Grade completion: Grade completion is defined by the grade in school completed by the child at age 15. For this part of the analysis, we consider both OC children and YC children when they are of age 15 and look at their grade completion. Children from OC reach 15 years of age in round 3 of the survey while children from YC reach 15 years of age in round 5 of the survey. We, therefore, consider grade completion in round 3 for OC children and that in round 5 for YC children. Table 4 shows grade attainment at age 15 by cohort.

Table 4: Grade attainment at age 15 by cohort

	Young Cohort		Old Cohort	
	Mean	SD	Mean	SD
Grade attainment at age 15	8.34	1.39	8.15	1.72
N	1822		961	

Table 5: Prevalence of health shock as percentage of households

	2007	2009-10	2013-14	2016-17
Health shock to child	29.33	18.91	31.64	39.93
N	1950	1930	1915	1893
Health shock to parent	14.56	12.48	17.02	19.73
N	1950	1930	1915	1900

Table 6: Descriptive statistics

	Health shock to child				Health shock to parents			
Variable	Yes		No		Yes		No	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Age of the oldest parent	38.68	6.48	38.02	6.36	38.74	6.40	38.12	6.41
Age of child (in months)	128.25	46.32	117	43.3	127.04	45.12	119.15	44.31
Consumption	8811	8358	8011	7751	8635.42	7323.72	8181.61	8066.48
Wealth index	.54	.19	.55	.18	.53	.18	.55	.19
Size of landholding	2.15	4.67	1.71	3.76	1.61	2.88	1.88	4.23
	Yes		No		Yes		No	
	Percentage		Percentage		Percentage		Percentage	
Health facility	37.4		41		38		40	
Livestock ownership	45.8		38.8		42.4		40.7	
N=		7696						

3.5 Health shock variable

We consider two types of health shock variables: health shock to child, and health shock to parents. Health shock to child is a binary variable that indicates whether the YL child has faced any illness since the previous round of survey. Due to restrictions imposed by data, we have considered injury instead of illness in round 3. Health shock to parents is a binary variable that indicates whether YL child's parents have experienced illness since the last round of survey. Table 5 shows prevalence of child health shock and parental health shock across survey years.

Table 6 shows characteristics of households that experienced health shock to child compared to those which did not experience health shock to child

Table 7 shows distribution of standardized PPVT score across survey rounds with respect to prevalence of health shock.

Table 8 shows distribution of grade completion at age 15, across cohorts with respect to

Table 7: Standardized PPVT score across survey years

	Child health shock				Parental health shock			
	Yes		No		Yes		No	
Standardized PPVT score	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2007	-0.63	0.99	-0.79	0.92	-0.85	0.76	-0.73	0.97
2009-10	0.38	1.16	0.70	1.40	0.33	1.22	0.68	1.37
2013-14	-0.09	0.34	-0.03	0.35	-0.04	0.33	-0.05	0.35
2016-17	0.15	0.34	0.13	0.35	0.12	0.37	0.14	0.34

Table 8: Grade completion at age 15

	Child health shock				Parental health shock			
	Yes		No		Yes		No	
Grade attainment at age 15	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Young Cohort	8.27	1.41	8.46	1.34	8.28	1.52	8.38	1.29
Old Cohort	7.80	1.86	8.37	1.58	8.13	1.75	8.21	1.63

prevalence of health shock.

4. Empirical specification

To answer whether public health insurance can mitigate adverse impact of health shock on children's educational outcome, we examine the interactions between access to public health insurance and incidence of health shock. We exploit the staggered roll out of Rajiv Aarogyasri (RAS), a publicly financed health insurance. In particular we look at the interaction of the RAS exposure variable and health shock variable. The coefficient on the interaction term is expected to give us the effect of mitigation of RAS. Our empirical specification is based on the following difference-in-difference framework: a child with experience of health shock will have worse cognitive and educational outcome than a child without experience of health shock. Thus the difference in outcome between the former and the latter will be negative. However, if the RAS is able to mitigate this negative impact of health shock, this difference would be smaller for households with high exposure to RAS compared to households with low exposure to RAS. Thus we expect our difference-in-difference estimator to be positive. We look at the mitigating role of RAS for child health shock and parental health shock separately. Furthermore, we look at the effect on PPVT scores and grade attainment under different specifications.

4.1 Effect of health shock and RAS exposure on PPVT score

We look at the role of RAS in mitigating the adverse impact on PPVT scores with a TWFE regression. In our specification, "months of exposure" is a continuous treatment. Due to limited sample size of OC children, we limit our analysis to YC children.

$$PPVT_{idt} = \beta_0^1 + \beta_1^1 Childhealthshock_{it} + \beta_2^1 Childhealthshock_{it} * Monthsofexposure_{dt} + \beta_3^1 Monthsofexposure_{dt} + \alpha_i^1 + \tau_t^1 + u_{it}^1 \quad (1)$$

$$PPVT_{idt} = \beta_0^2 + \beta_1^2 Parentalhealthshock_{it} + \beta_2^2 Parentalhealthshock_{it} * Monthsofexposure_{dt} + \beta_3^2 Monthsofexposure_{dt} + \alpha_i^2 + \tau_t^2 + u_{it}^2 \quad (2)$$

Equation 1 shows the effect of child health shock, when interacted with exposure to RAS, on standardized PPVT score of the child. The variable $Childhealthshock_{it}$ is a binary variable that indicates whether ith child has faced health shock in round t.The coefficient β_1^1 captures the effect of a health shock on PPVT scores of the child. The variable $Monthsofexposure_{dt}$ is a continuous variable that measures months of exposure to RAS in district d in round t.Its coefficient β_3^1 captures the effect of one additional month of exposure on PPVT score of the child. The interaction term $Childhealthshock_{it} * Monthsofexposure_{dt}$ is the variable of interest and its coefficient β_2^1 measures the extent of mitigation by RAS. A negative sign of β_1^1 and a positive sign of β_2^1 would indicate child health shock has negative impact on PPVT score of the child, which is mitigated by exposure to RAS. We further supplement our specification with child fixed effects and survey-round fixed effects to control for child specific time invariant characteristics, and year specific characteristics respectively. The child fixed effects account for the fact that children from vulnerable households can have poorer health to begin with and may be more likely to experience health shocks.

Equation 2 shows the effect of parental health shock, when interacted with exposure to RAS, on standardized PPVT score of the child. The variable $Parentalhealthshock_{it}$ is a binary variable that indicates whether parents of ith child has faced health shock in round t.The coefficient β_1^2 captures the effect of a parental health shock on PPVT scores of the child. The variable $Monthsofexposure_{dt}$ is a continuous variable that measures months of exposure to RAS in district d in round t.Its coefficient β_3^2 captures the effect of one additional month of exposure on PPVT score of the child. The interaction term $Parentalhealthshock_{it} * Monthsofexposure_{dt}$ is the variable of interest and its coefficient β_2^2 measures the extent of mitigation by RAS. A negative sign of β_1^2 and a positive sign of β_2^2 would indicate parental health shock has negative impact on PPVT score of the child, which is mitigated by exposure to RAS. We further supplement our specification with child fixed effects and survey-round fixed effects to control for child specific time invariant characteristics, and year specific characteristics respectively. The child fixed effect, in this case, accounts for the fact that children from vulnerable households may be more likely to experience parental health shocks.

4.2 Effect of health shock and RAS exposure on grade completion at age 15

We look at the role of RAS in mitigating the adverse impact on grade attainment using a fixed effects estimation. Health shock and insurance exposure is expected to have a cumulative impact on grade attainment. Based on this understanding, we take a cross-section of children at age 15 and look at cumulative effect on grade attainment at that age, following Duflo (2001). Pursuant to the literature on early life shocks and UNESCO classification[1], we divide childhood into early childhood (ages 0-8) and later childhood (ages 8-15) and study the impacts of health shock and health insurance exposure separately for these two age groups.Ideally we would have liked to consider each period in a child's early childhood and later childhood and compare a child who has experienced a health shock but has a shorter exposure to health insurance with another child who has experienced health shock but has had a longer exposure to health insurance during the same period. However, owing to timing of the program roll out, our health insurance exposure variable varies only from ages 5 to 15 for the Young Cohort (YC) children and from ages 12 to 15 for Old Cohort (OC) children. Thus, we also consider our analyses separately for YC and OC children.

4.2.1 Child health shock

We study the impact of child health shock and health insurance exposure for YC with the following specifications:

$$grade^{15}_{id_{YC}} = \beta^3_0 + \beta^3_1 CoveredChildhealthshock^{5-8}_{id_{YC}} + \beta^3_2 Childhealthshock^{5-8}_{i_{YC}} + \alpha^3_d + u^3_{id} \tag{3}$$

$$grade^{15}_{id_{YC}} = \beta^4_0 + \beta^4_1 CoveredChildhealthshock^{8-15}_{id_{YC}} + \beta^4_2 Childhealthshock^{8-15_{YC}}_{i} + \alpha^4_d + u^4_{id} \tag{4}$$

Equations 3 and 4 capture the effect of covered child health shock on grade completion at age 15 for YC children. Our dependent variable $grade^{15}_{id_{YC}}$ measures the total number of grades completed by i^{th} child of YC residing in d^{th} district at age 15. We divide childhood into two key periods of exposure, in line with Gunnsteinsson et al.(2014). These two vital periods of exposure are: early childhood, which includes ages 5 to 8 for our purpose, and late childhood, which includes ages 8 to 15. Equation 3 captures the effect of health shock and health insurance exposure during ages 5-8, while equation 4 captures the effects of health shock and health insurance exposure during ages 8-15. The variables $Childhealthshock^{5-8}_{i_{YC}}$ and

[1] https://www.unesco.org/en/education/early-childhood

$Childhealthshock^{8-15}_{i_{YC}}$ are binary variables that indicate whether child has faced health shock during ages 5-8 and 8-15 respectively. The coefficients β^3_2 and β^4_2 capture the effects of experiencing health shock during these ages. The variable $CoveredChildhealthshock^{5-8}_{id_{YC}}$ measures the cumulative months of exposure enjoyed by a child i in d^{th} district at age 8 who has faced health shock between the ages 5 and 8. Similarly, the variable $CoveredChildhealthshock^{8-15}_{id_{YC}}$ measures the cumulative months of exposure enjoyed by a child i in d^{th} district at age 15 who has faced health shock between the ages 8 and 15. The coefficients β^3_1 and β^4_1 capture the effects of an additional month of RAS exposure for a health shock affected child. The variables $CoveredChildhealthshock^{5-8}_{id_{YC}}$ and $CoveredChildhealthshock^{8-15}_{id_{YC}}$ are our variables of interest. A positive sign of β^3_1 along with a negative sign of β^3_2 would indicate that while experiencing a health shock during the ages 5-8 will have cumulative negative impact on grade attainment at age 15, exposure to RAS will mitigate some of the adverse effect. Similarly, a positive sign of β^4_1 along with a negative sign of β^4_2 would indicate that while experiencing a health shock during the ages 8-15 will have cumulative negative impact on grade attainment at age 15, exposure to RAS will mitigate some of the adverse effect. Through this specification, we compare a YC child who had experienced health shock during the ages 5-8 (8-15) and had a longer exposure to RAS with a child who had experienced health shock during the same period but had a shorter exposure to RAS. Since RAS was first introduced in backward districts, children experiencing longer exposure to RAS can be located in poorer districts and can have worse educational outcomes. To control for this, we further supplement our empirical specification with district fixed effects.

We study the impact of child health shock and health insurance exposure for OC with the following specifications:

$$grade^{15}_{id_{OC}} = \beta^5_0 + \beta^5_1 CoveredChildhealthshock^{12-15}_{id_{OC}} + \beta^5_2 Childhealthshock^{12-15}_{i_{OC}} + \alpha^5_d + u^5_{id} \tag{5}$$

Equation 5 captures the effect of covered child health shock on grade completion at age 15 for OC children. Our dependent variable $grade^{15}_{id_{OC}}$ measures the total number of grades completed by i^{th} child of OC residing in d^{th} district at age 15. The variable $Childhealthshock^{12-15}_{i_{OC}}$ is a binary variable that indicates whether child has faced health shock during ages 12-15. The coefficient β^5_2 captures the effects of experiencing health shock during these ages. The variable $CoveredChildhealthshock^{12-15}_{id_{OC}}$ measures the cumulative months of exposure enjoyed by a child i in d^{th} district at age 15 who has faced health shock between the ages 12 and 15. The coefficient β^5_1 captures the effects of an additional month of RAS exposure for a health shock affected child. The variables $CoveredChildhealthshock^{12-15}_{id_{OC}}$ is our variable of interest. A positive sign of β^5_1 along with a negative sign of β^5_2 would indicate that while experiencing a health shock during the ages 12-15 will have cumulative negative impact on grade attainment at age 15, exposure to RAS will mitigate some of the adverse effect. Through this specification, we compare a OC child who had experienced health shock during the ages 12-15 and had a longer exposure to RAS with a OC child who had experienced health shock during the same period but had a shorter exposure to RAS. Similar to YC, We further supplement our empirical specification with district fixed effects.

4.2.2 Parental health shock

Similar to child health shock, we look at the effects of parental health shock and RAS exposure on grade attainment at age 15 through the following specifications:

$$grade^{15}_{id_{YC}} = \beta^6_0 + \beta^6_1 CoveredParentalhealthshock^{5-8}_{id_{YC}} + \beta^6_2 Parentalhealthshock^{5-8}_{i_{YC}} + \alpha^6_d + u^6_{id} \tag{6}$$

$$grade^{15}_{id_{YC}} = \beta^7_0 + \beta^7_1 CoveredParentalhealthshock^{8-15}_{id_{YC}} + \beta^7_2 Parentalhealthshock^{8-15}_{i_{YC}} + \alpha^7_d + u^7_{id} \tag{7}$$

$$grade^{15}_{id_{OC}} = \beta^8_0 + \beta^8_1 CoveredParentalhealthshock^{12-15}_{id_{OC}} + \beta^8_2 Parentalhealthshock^{12-15}_{i_{OC}} + \alpha^8_d + u^8_{id} \tag{8}$$

In these specifications, $grade^{15}_{id_{YC}}$ and $grade^{15}_{id_{OC}}$ are the dependent variables. Equations 6 and 7 are for YC children and equation 8 is for OC children. For YC, the variables of interest are $CoveredParentalhealthshock^{5-8}_{id_{YC}}$ and $CoveredParentalhealthshock^{8-15}_{id_{YC}}$, while for OC, variable of interest is $CoveredParentalhealthshock^{12-15}_{id_{OC}}$.
$CoveredParentalhealthshock^{5-8}_{id_{YC}}$ and $CoveredParentalhealthshock^{8-15}_{id_{YC}}$ measure the months of exposure enjoyed by a YC child who has experienced parental health shock during ages 5-8 and 8-15 respectively. Similarly, $CoveredParentalhealthshock^{12-15}_{id_{OC}}$ measures the months of RAS exposure enjoyed by OC child who experienced parental health shock during ages 12-15. The coefficients of interest for YC are β^6_1 and β^7_1, while that for OC is β^8_1.

5. Results

5.1 Effect of health shock and RAS exposure on PPVT score

Table 9 shows the effects of child health shock and RAS exposure on standardized PPVT score of child. Experience of health shock by the child is found to increase standardized

PPVT score by 0.247 standard deviations. The interaction between child health shock and months of exposure indicates that for children who have faced health shock, one month increase in exposure to RAS, reduces standardized PPVT scores by 0.002 standard deviations. Such a finding seems apparently counter intuitive as a health shock is found to improve cognitive performance. However, we provide suggestive evidence later in the paper that such a counter intuitive finding can be explained by looking at how parental investments respond to child health shock.

Table 9: Effect of child health shock and RAS exposure on PPVT score

	(1) Standardized PPVT score
child health shock	0.247**
	(0.0934)
months of exposure	0.0177
	(0.0210)
child health shock X months of exposure	-0.00201*
	(0.000977)
4.round	-0.579
	(1.636)
5.round	-1.000
	(2.390)
_cons	-0.826***
	(0.0841)
N	5640
Child FE	Yes
Round FE	Yes
Clustered SE	Yes
Control variables	No

Standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 10 shows the effects of parental health shock and RAS exposure on standardized PPVT score of child. Experience of parental health shock by a child reduces standardized PPVT scores by 0.195 standard deviations. The interaction between parental health shock and months of exposure indicates that for a child who has experienced parental health shock, an additional month of exposure to RAS improves standardized PPVT scores by 0.002 standard deviations. Such a finding implies that adverse impact of experiencing parental health shock on cognitive performance is partially mitigated by availability of RAS.

Table 10: Effect of parental health shock and RAS exposure on PPVT score

	(1) Standardized PPVT score
parental health shock	-0.195**
	(0.0801)
months of exposure	0.00768
	(0.0197)
parental health shock X months of exposure	0.00207**
	(0.000805)
3.round	1.179*
	(0.590)
4.round	0.105
	(1.535)
5.round	0.00854
	(2.248)
_cons	-0.724***
	(0.101)
N	7540
Child FE	Yes
Round FE	Yes
Clustered SE	Yes
Control variables	No

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

5.2 Effect of health shock and RAS exposure on grade completion at age 15

5.2.1 Child health shock

Tables 11 and 12 show the effects of child health shock and RAS exposure on grade completion of YC child at age 15. Table 11 shows the effect of health shock and RAS exposure during the ages 5-8, while table 12 capture the effect for health shock and exposure experienced during ages 8-15. Experience of health shock during the ages 5-8 reduces grade attainment at 15 by 0.741 grades. However, for a child who has experienced health shock during this period, and additional month of exposure to RAS improves grade attainment at age 15 by 0.03 grades. Thus exposure to RAS during the ages 5-8 for health shock affected children, is found to mitigate the cumulative adverse impact on grade attainment at age 15. On the other hand, experience of health shock during the ages 8-15 is not found to have any significant impact on grade attainment at age 15. For children affected by health shock, having an additional month of exposure to RAS is not found to have any significant impact on grade attainment at age 15. Our finding of health shock during early childhood years having cumulative adverse impact on grade attainment, while health shock during later childhood years not having any significant impact is consistent with the literature on early life shocks.

Table 11: Effect of child health shock and RAS exposure on grade attainment: ages 5-8

	(1) Grade attainment at age 15
Covered health shock to child during 5-8 years age	0.0301**
	(0.0125)
Health shock to child during 5-8 years age	-0.741**
	(0.310)
_cons	8.337***
	(0.0573)
N	1833
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	YC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 13 shows the effects of child health shock and RAS exposure on grade completion of OC child at age 15. Experience of health shock during the ages 12-15 is not found to have any significant impact on grade attainment at age 15. For children who have experienced health shock during the ages 12-15, an additional month of RAS exposure is not found to

Table 12: Effect of child health shock and RAS exposure on grade attainment: ages 8-15

	(1)
	Grade attainment at age 15
Covered health shock to child during 8-15	-0.0117
	(0.00974)
Health shock to child during 8-15	1.295
	(1.075)
_cons	8.346***
	(0.0775)
N	1837
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	YC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

have any significant impact on grade attainment. This is consistent with the findings of the early life literature that shocks which are experienced in early childhood, rather than later in the childhood have far greater future implications.

5.2.2 Parental health shock

Tables 14 and 15 show the effects of parental health shock and RAS exposure on grade completion of YC child at age 15. Table 14 shows the effect of parental health shock and RAS exposure during the ages 5-8, while table 15 capture the effect for parental health shock and exposure experienced during ages 8-15. Experience of parental health shock during the ages 5-8 is not found to have any significant impact on grade attainment at age 15. For a child who has experienced parental health shock during this period, and additional month of exposure to RAS is not found to have any significant impact on grade attainment at age 15. Similarly, experience of parental health shock during the ages 8-15 is not found to have any significant impact on grade attainment at age 15. For children affected by parental health shock during this period, having an additional month of exposure to RAS is not found to have any significant impact on grade attainment at age 15. Thus parental health shock is not found to have any cumulative impact on grade attainment at age 15 for YC children.

Table 16 shows the effects of parental health shock and RAS exposure on grade completion of OC child at age 15.Experience of parental health shock during the ages 12-15 is not found to have any significant impact on grade attainment at age 15. For children who have experienced parental health shock during the ages 12-15, an additional month of RAS exposure is not

Table 13: Effect of child health shock and RAS exposure on grade attainment: ages 12-15

	(1) Grade attainment at age 15
Covered health shock to child during 12-15 years	-0.0236
	(0.0200)
health shock to child during 12-15 years	0.0554
	(0.457)
_cons	8.260***
	(0.0848)
N	964
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	OC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 14: Effect of parental health shock and RAS exposure on grade attainment: ages 5-8

	(1) Grade attainment at age 15
Covered parental shock to child during 5-8	0.00440
	(0.0183)
parental shock to child during 5-8	-0.0556
	(0.507)
_cons	8.336***
	(0.0596)
N	1833
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	YC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 15: Effect of parental health shock and RAS exposure on grade attainment: ages 8-15

	(1)
	Grade attainment at age 15
Covered parental shock to child during 8-15	-0.00701
	(0.0142)
parental shock to child during 8-15	0.707
	(1.540)
_cons	8.364***
	(0.0740)
N	1837
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	YC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

found to have any significant impact on grade attainment. Thus parental health shock is not found to have any cumulative impact on grade attainment at age 15 for OC children.

6. Underlying mechanism

In this section we offer suggestive evidence that an improvement in standardized PPVT scores following experience of a health shock by the child is brought about through increased spending on education and health by household. Due to data limitation we are unable to use spending on the Young Lives child and therefore consider the effect on household spending, controlling for the presence of siblings. Table 17 shows association between household spending on education and health and health shock of the child. While the coefficients on child health shock is not significant, they are quite large, indicating a large and positive correlation between health shock of the child and household spending on education and health. The large coefficient sizes are obtained despite controlling for presence of siblings. The coefficients on child health shock are however imprecisely estimated. Such a finding is consistent with compensating parental investment discussed in the literature (Halla & Zweimuller,2014; Bharadwaj et al.,2018; Nicoletti & Tonei;2020)

Table 16: Effect of child health shock and RAS exposure on grade attainment: ages 12-15

	(1)
	Grade attainment at age 15
Covered health shock to child during 12-15 years	-0.0236
	(0.0200)
health shock to child during 12-15 years	0.0554
	(0.457)
_cons	8.260***
	(0.0848)
N	964
District FE	Yes
Clustered SE	Yes
Control variables	No
Cohort	OC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 17: Effect of child health shock on education and health spending

	(1)	(2)	(3)
	HH spending on school and books	HH spending on tuition	HH spending on healt
child health shock	847.8	347.9	882.5
	(949.6)	(719.0)	(969.5)
sibling	-43.76	783.1	-2050.3**
	(1946.7)	(1740.1)	(953.9)
4.round	8328.4***	2533.3***	4004.3***
	(1662.3)	(774.9)	(643.2)
5.round	15036.4***	4121.2***	8892.4***
	(1974.8)	(1289.4)	(1783.5)
_cons	1909.0	-650.2	5272.1***
	(2548.6)	(1560.1)	(891.5)
N	5540	2396	5372
Child FE	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Control variables	No	No	No
Cohort	YC	YC	YC

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

7. Conclusion

The paper sought to answer whether public health insurance schemes can mitigate adverse impact of health shock on children's educational outcome. Existing literature has documented extensively the long term impact of early life circumstances. However, whether effects of adverse early life circumstances can be mitigated is less studied. In this context, we looked at the plausibly mitigating role of a publicly financed health insurance scheme in the Indian states of Andhra Pradesh and Telengana. We exploited the staggered roll out of Rajiv Aarogyasri (RAS), a publicly financed health insurance scheme. The staggered roll out of RAS generates variation in months of exposure to the scheme across survey years and districts of residence. Combining a panel data from the Young lives India with administrative records, we employ a difference in difference framework to study the interaction between experience of health shock and health insurance availability. In this context we make a distinction between health shock to child, and health shock to parents. We consider two measures of educational outcomes: PPVT scores of the child, and grade attainment at age 15.

We find that exposure to parental health shock in childhood has no effect on grade attainment at age 15. On the other hand, exposure to child health shock during the age 5-8, has negative impact on grade attainment at age 15, which is partially mitigated by health insurance availability. Child health shock in later childhood, however, is not found to have any impact on child's grade attainment at age 15.We also find that exposure to parental health shock adversely affects a child's cognitive outcomes, which is partially mitigated by health insurance availability. In contrast, exposure to child health shock improves the child's cognitive outcome. In this context, we provide suggestive evidence that the positive impact of child health shock on cognition is driven by compensating parental investment on education and health of the shock affected child.

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