Health Coverage and Educational Investments*

ABSTRACT

The human capital theory asserts that expenditures on health and education are complementary investments. As such, health investments increase education demand, thereby increasing educational expenditures. This paper examines the impact of health insurance on three aspects of a household's demand for education: (a) the share of educational expenditures; (b) the actual educational expenditures; (c) the probability of taking out an educational loan. Drawing on a health insurance scheme in India, this paper uses a modified difference-in-difference strategy and two waves of the Indian Human Development Survey (2004-05 and 2011-12) and finds an increase of 10 percent in the share of educational expenditures, a 39 percent increase in actual expenditures, and a 185 percent increase in the likelihood of obtaining educational loans during the period. It is more pronounced among households living below the poverty line. All results are robust to changes in subsamples.

Keywords: Human capital investments, Health insurance, treatment effect, difference-in-differences

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1 Introduction

Health policies target health outcomes. For instance, a government's spending on health aims to reduce the number of deaths from a particular disease or the number of people deprived of essential healthcare services. The success or failure of such policies predominantly depends on the improvements in health outcomes. There is a large body of research that examines the impact of such health policies on health outcomes. However, there exists no study, to our knowledge, that evaluates the impact of health interventions on educational investments[1]. This paper fills this void. It examines the impact of health insurance on households' educational investments. The results suggest that health coverage in Andhra Pradesh (AP) increases the share of education in the household's monthly per capita consumption expenditure by 10%, the real monthly per capita education expenditure by 39% and the likelihood of taking an educational loan by 185%.

Although there has been a gradual increase in global expenditure on education, the education system worldwide is still largely underfunded. While the government has historically been a major contributor to education funding, sponsoring more than three-quarters of global education spending, it too is grappling with severe fiscal challenges after the 2008 economic crisis[75][74]. Over the last decade, the government's contribution to education as a share of its total budget remained stagnant, varying between 7% in Italy and 17% in Chile across OECD countries, and fell short of the international benchmarks (15-20%) set by UNESCO in most countries[58][76]. Lately, the annual gap in education funding has been estimated at US $148 billion for low and lower middle income countries and US $150 billion for the United States[27][73].

While it's evident that education requires a substantial boost in the allocation of government budgets, it's equally vital that attention is devoted to the health sector. Health expenses have surged substantially in recent years. The average spending on health per person more than doubled between 2009 and 2019, from US $17.1 to US $39.3 for low income countries, and from US $1146 to US $2937

[1]There are studies exploring the impact of health interventions on educational attainment, not on educational investments (Oreopoulos et al. (2008); Barreca (2010); Black et al. (2007); Ojha (2022); Liu (2016)).

for high income countries[80]. Like education, public spending on health is trailing behind international benchmarks. In 2019, the average government health expenditure as a percentage of GDP[2] by countries worldwide stood at 5.89%, which is short by at least 1% percentage point from the standards required to achieve universal health coverage[62][64].

Clearly, with tightening government budgets, there prevails a trade off between public spending on education and health. This paper proposes a collaborative approach where both sectors receive the necessary support. While the government can continue allocating resources to support the health sector, a portion of funding for education can be drawn from private sources. Specifically, households can contribute towards the much needed additional education funding. Evidence suggests that households are an important contributor to education spending in low and middle income countries, and devoted on average 3.2% of their household budget to education in the 2010s[75]. The share ranged from less than 1% in southeastern European countries to more than 6% in sub-Saharan countries. In the United States, the share of education in annual household expenditure remained low at about 2% between 2018-2021[49]. This paper explores the idea whether health coverage can incentivize households to invest more in education, guided by the theory in human capital literature. Thereby, countries can ensure health and education simultaneously through better targeting of health coverage policies.

We compare the estimates of educational investments for households with access to health coverage to the estimates for households without access to health coverage. The difference between the two estimates yields the effect of health coverage on educational investments. The main identification issue with the comparison of households with and without health coverage is that the households with higher risk aversion or other unobserved characteristics may self-select themselves into health coverage programs.

To deal with the selectivity issue in health coverage, we utilize a novel intervention in India - Rajiv Aarogyasri Health Insurance Scheme (Aarogyasri). Aarogyasri is a government sponsored health insurance scheme launched in 2007 for the poor in the state of Andhra Pradesh in India. Compared

[2]Includes internal transfers and grants, subsidies to voluntary health insurance beneficiaries, NPISH or enterprise financing schemes as well as compulsory prepayment and social health insurance contributions.

to the health insurance schemes introduced by other Indian states, Aarogyasri is attractive for this analysis for the following reasons. First, Aarogyasri increased health coverage to over 90% families in Andhra Pradesh, which is considerably higher than the coverage of health insurance schemes introduced by other Indian states (Table 10)[3]. This allows us to consider the entire state of Andhra Pradesh as the treatment group, and overcome the confounding effect of any selectivity issue in access to public health coverage. Second, Aarogyasri pioneered cashless healthcare in India. Prior to Aarogyasri, the prevalence of health insurance coverage in Andhra Pradesh and other Indian states was relatively low. In 2004-05, only 1.7% of the families in Andhra Pradesh had access to private or public health coverage[4]. This condition provides an advantageous setting for estimating the scheme's effects without potential bias stemming from pre-existing insurance coverage. Third, the scheme uniquely covers the cost of transportation home post discharge from the hospital. This mitigates the distance to the hospital from home as a participation barrier in the scheme. Furthermore, an extensive network of empanelled hospitals (454 hospitals) and comprehensive treatment coverage (938 procedures) provided by the scheme act as positive incentives, further stimulating participation.

The estimation is performed using panel data from the 2004-05 and 2011-12 rounds of the India Human Development Survey (IHDS). The estimation strategy compares the households in Andhra Pradesh to the households in all other states of India, using a modified difference-in-difference setting. However, we exclude the states that launched their own state health insurance schemes between 2004-05 and 2011-12[5] and outliers[6] from the control group. The main identification assumption is that the temporal changes in educational investments of the households in Andhra Pradesh and other states were similar before the launch of Aarogyasri. The panel data structure of IHDS is exploited to control for household-level fixed effects. The possibility of correlation between the unobserved determinants of the educational investments-related outcomes is dealt with by estimating the system of equations simultaneously using the Seemingly Unrelated Regression (SUR) method. Later, we test the strength of the main results using various robustness checks and placebo tests.

[3]The eligibility for being covered under the scheme is Below Poverty Line (BPL) ration card holding by the family.

[4]The corresponding figure for other Indian states is 2.5%. These are the author's own computations using data from IHDS 2004-05

[5]Tamil Nadu, Maharashtra, Gujarat, Kerala, Karnataka, and West Bengal

[6]Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Assam, Goa, and all union territories (Chandigarh, Daman Diu, Dadra & Nagar Haveli and Pondicherry)

The key empirical finding is that Aarogyasri led to a significant increase in the educational investments of households in Andhra Pradesh. The increase in educational expenditures of the poorest households is twofold the average for Andhra Pradesh. The results are robust to different subsamples and specifications and add to the literature on the unintended benefits of public health insurance programs.

The paper makes a valuable contribution to the ongoing debate that has persisted for quite some time regarding the direction of causality between health and education. The relationship between health and education is one of the most fundamental and comprehensively studied relationships in the field of health economics. The relationship has been suggested to be mostly positive and statistically significant at 5 percent level, regardless of the measure of health[7] (Grossman and Kaestner (1997)). However, for the purpose of explaining the positive correlation between health and education, the causality running from schooling to health has been extensively studied in the literature[8], while the direction of causality running alternatively, that is, from better health to more education, is relatively less exploited. Several other studies scrutinize the role of 'third variables', like parental characteristics, mental ability, and time preference, in affecting both health and schooling in the same direction[9]. From the perspective of effective policy interventions, it's important to identify the direction of the causality. On that account, this paper attempts to fill the gap in the literature on inter-linkages between health and education by surveying the hypothesis on health interventions (here, public health insurance) creating a causal effect on educational outcomes (here, intra-household educational investment).

The paper also connects to the strand of literature examining the influence of household-level shocks on the redistribution of household resources allocated to educational investments. Previous research has investigated the effects of household-level income shocks such as conditional cash transfers, household remittances from overseas, and transitory income on the allocation of resources for education, as demonstrated in the studies by Duque et al. (2018), Beegle et al. (2006) and Yang (2008).

[7] Including mortality rates, morbidity rates, self evaluated health status, life expectancy, and physiological indicators of health.

[8] Grossman (1976); Grossman (2015); Meara et al. (2008); Stockwell (1963); Hinkle et al. (1968); Lleras-Muney (2005)

[9] Rozenzweig Wolpin (1994); Vikram et al. (2012); Pınar Mine Güneş (2015); Makate and Makate (2016); Grépin and Bharadwaj (2015); Arnaud et al. (2013); Belzil and Hansen (2002); John Hause (1972); Heckman and Vytlacil (2001); Ashenfelter and Rouse (1998); Becker and Mulligan (1997); Fuchs (1982)

Within the context of household-level health shocks, Liu (2016) and Aaskoven et al. (2022) have explored the repercussions on educational attainment and learning outcomes. This paper, however, distinguishes itself by examining the consequences of unforeseen access to public health coverage on the intra-household allocation of resources for education, focusing on an Indian context.

The paper proceeds as follows: Sections 2 and 3 examine the theoretical predictions on the effect of health coverage on educational investments. Section 4 provides a background of the public health insurance scheme used as treatment in the study. Section 5 describes the data set used for the analysis. Section 6 summarises the experimental design and descriptive statistics. Section 7 outlines the empirical strategy and the identifying assumptions. Section 8 presents the results, robustness checks, and placebo tests performed. Section 9 concludes. All graphs and tables have been presented in the appendix.

2 The Theory

Human capital investments include investments in health (Becker (2007)). Investing in one's health improves one's survival probability, thereby extending one's longevity. As longevity increases, education expenditures are likely to rise since educational investments will yield returns for a longer period of time (Becker (1964); Mincer (1958)). Considering that free health insurance increases longevity without increasing health expenditure, it seems likely that such insurance will encourage early investment in education.

Research on health insurance focuses primarily on self-protection. People take measures not only to improve their health condition but also to avoid health shocks by using medical and nonmedical methods such as insurance (Cutler et al. (2000)). In contrast, the complementarities in health insurance and education have been less explored. We demonstrate these complementarities based on the framework proposed by Becker (2007).

Consider a 2-period model (Becker, 2007) where an individual i lives for two periods (0 and 1). Let $u[.]$ denote the utility function of i. Thus, the utility of i in period 0 and period 1 are $u_i[x_0, l_0]$ and $u_i[x_1, l_1]$, respectively, where x is the expenditure on goods apart from education and l is leisure hours.

Given these utilities, the present discounted value is

$$V = u[x_0, l_0] + \beta S(I) u[x_1, l_1] \tag{1}$$

where β and $S(I)$ represent the time discount rate, and probability of survival in period 1, respectively. $S(I)$ depends on whether an individual has access to insurance I such that $\partial S(I)/\partial I > 0$, i.e., health insurance raises the probability of survival.

The budget constraint is

$$x_0 + S(I)\frac{x_1}{(1+r)} + E = w_0(1 - l_0) + S(I)\frac{w_1(E)(1 - l_1)}{(1+r)} \tag{2}$$

The left hand side of this equation denotes x expenditure on goods apart from education (assuming unitary prices), and E educational expenditure. The right hand side represents the total wealth accumulated from income in both periods. Here r represents the interest rate, and w_0 and $w_1(E)$ represent the wage rate in periods 0 and 1, respectively. The wage rate in period 1 is a function of education expenditure.

The optimal choice of educational expenditure emerges from the following utility maximization problem.

$$\begin{aligned} &\text{Maximize} : V = u[x_0, l_0] + \beta S(I) u[x_1, l_1] \\ &\text{subject to} : x_0 + S(I)\frac{x_0}{(1+r)} + E = w_0(1 - l_0) + S(I)\frac{w_1(E)(1 - l_1)}{(1+r)} \end{aligned} \tag{3}$$

The F.O.C. with respect to E is

$$S(I)\frac{\partial w_1(E)}{\partial E}\frac{(1 - l_1)}{(1+r)} - 1 = 0 \tag{4}$$

The effect of I on E thus can be determined by

$$S^{'}(I)\frac{\partial w_1(E)}{\partial E}\frac{(1-l_1)}{(1+r)}+S(I)\frac{\partial^2 w_1(E)}{\partial E^2}\frac{\partial E}{\partial I}\frac{(1-l_1)}{(1+r)}-0=0 \tag{5}$$

Simplifying

$$\frac{\partial E}{\partial I}=-\frac{S^{'}(I)}{S(I)}\frac{\partial w_1(E)/\partial E}{\partial^2 w_1(E)/\partial E^2} \tag{6}$$

Considering the evidence on sheepskin effect in returns to education (Hungerford and Solon (1987); Jaeger and Page (1996)), there are positive returns to schooling, i.e., $\partial w_1(E)/\partial E > 0$. Hence, the sign of $\partial E/\partial I$ depends on the sign of $\partial^2 w_1(E)/\partial E^2$. If the returns to schooling rise at an increasing rate, i.e., $\partial^2 w_1(E)/\partial E^2 > 0$, one would always stay in school and never quit school. This is unlikely to happen. Therefore, $\partial^2 w_1(E)/\partial E^2 < 0$ and the condition that $\partial E/\partial I > 0$ is satisfied.

3 Potential Channels

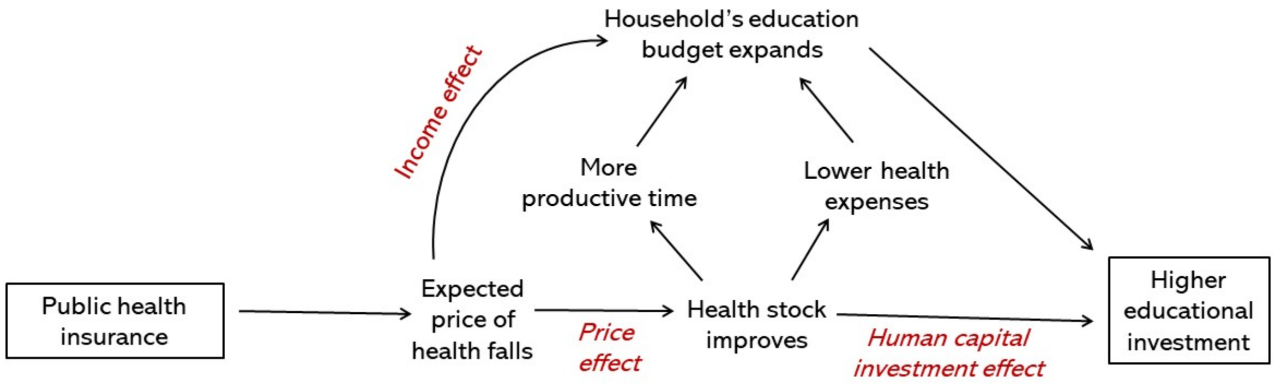

Figure 1: Directed Acyclic Graph Illustrating the Causal Relationship between Health Insurance and Educational Investments

Health insurance (here, Aarogyasri) is likely to cause an increase in the educational investment of a household through three plausible channels. We represent the three channels using a directed acyclic graph (DAG) (Pearl, 1995) in Figure 1. A description of the graph follows.

The first channel relates to the price effect of health insurance on the demand for health, based on the model of health demand by Grossman (1972). Demand for health is a factor of healthcare services, past health records, healthy behaviors, etc. Health insurance makes healthcare services cheaper. As a result, assuming healthcare to be a normal good, the demand for healthcare services rises. This phenomenon is substantiated by numerous studies that have explored the association between having health insurance coverage and the utilization of healthcare services (Card et al. 2008). An increment in health input (healthcare services) improves health.

Improved health increases the household's resources available for education in two ways. Firstly, better health reduces the need for healthcare and hence, lowers the household's current health expenditure. Lesser health expenses imply more resources available for other goods including education. Secondly, healthier people can work for longer hours and generate additional income for consumption. The rationale for this argument comes from the human capital model by Grossman (1972). The model considers health as an input into productive time, which is useful for generating earnings (assuming that the return from market activities is higher than non-market activities). The additional earnings are expected to expand the household's budget for education.

Improved health also increases the life span of an individual as healthier individuals tend to live more. This forms the second channel relating to the complementarities between health and schooling in human capital theory. A longer life span leads to higher investment in education (schooling and on-the-job training) as the returns are reaped over a longer time period (Mincer (1958); Becker (1964); Ben-Porath (1967)). Becker (2007) focuses on later ages and shows that a higher probability of survival at later ages increases the investment in education as the returns to education are reaped at later ages.

The third channel relates to the income effect of health insurance on the demand for education. In the absence of health insurance coverage, a person faces the risk of unforeseen health expenditures. Anticipation of unforeseen health expenditure increases household precautionary savings (Hubbard et al. (1995); Kotlikoff (1986)) and, thus, constrains the household's consumption budget for other commodities besides healthcare (assuming the ability to finance healthcare by borrowing is limited). Besides, rising health expenses are compensated with a reduced share of non-food items in the consumption bundle of a household, and education expenditure faces a major brunt. Liu (2016) shows that a 10 percentage point increase in health shock of uninsured households is associated with a 6 percentage point reduction in school enrolment to maintain household consumption. Accordingly, health insurance reduces the exposure to the risk of out-of-pocket health expenditure and releases household resources for non-medical goods including education. The findings in Bai and Wu (2014), Wagstaff and Pradhan (2005), Gruber and Yelowitz (1999), and other studies provide evidence of a decrease in private savings and an increase in non-medical consumption expenditure with access to health insurance.

The effect of the first and the third channels could be either positive or negative. The reason is that households can utilize the additional resources provided by health insurance for the consumption of non-medical goods other than education. Therefore, the final impact of health insurance on educational investments, determined by the combined effect of the three channels, is ambiguous. This paper analyses the combined effect empirically and provides evidence on its sign and magnitude. The paper also attempts to segregate the human capital investment effect and the price effect.

4 Background on Rajiv Aarogyasri Scheme

Rajiv Aarogyasri Health Insurance, commonly known as Aarogyasri, is a public health insurance programme, launched by the state government of Andhra Pradesh in India on 1st April 2007. The scheme aims to provide health coverage to poor households in Andhra Pradesh. All family members of a household holding a below poverty line ration card[10] are eligible to seek treatment under Aarogyasri, with no limit on the size of the household. The online database of the Civil Supplies department of the government of Andhra Pradesh is used to identify and authenticate beneficiaries. Aarogyasri played a pivotal role in ensuring healthcare access to the poor. By 2011-12, the scheme covered 198 lakh families (Table 7),i.e., 90% of the families in Andhra Pradesh.

The scheme was launched in two phases. The first phase of the scheme, Aarogyasri-I, was set forth on a pilot basis in three districts of Andhra Pradesh, including Mahboobnagar, Anantapur, and Srikakulam. The scheme was subsequently extended to other districts in the second phase[11]. The method of deciding the order of districts for the implementation of the scheme is unknown as per the currently available official sources. However, a study by Fan et al. (2012) mentions that the districts were chosen based on human development indicators, with the backward ones given priority. The study notes that the districts selected in the first phase were considered the most backward and balanced in the three regions of the

[10] including White Card (WAP), Antyodaya Anna Yojana card (AAY), Annapurna card (AAP)

[11] Table 5 and Table 6 provide details on various phases for the implementation of Aarogyasri. Figure 9 presents the five phases graphically.

state - Telangana, Rayalaseema, and coastal Andhra. The second phase of the scheme, Aarogyasri-II, was launched on 17th July 2008, as a build-up on Aarogyasri-I by including additional surgical and medical diseases. Post the launch of Aarogyasri-II, it was no longer permissible for poor families to demand relief for medical purposes under the Chief Minister's Relief Fund (CMRF) as earlier.

The scheme is designed such that the state government fully pays the insurance premium to the insurance company. Each poor household is provided with insurance coverage of 2 lakh Indian rupees per annum. The hospital bill is paid by the insurance company. That is, the scheme provides end-to-end cashless service to its beneficiaries. The beneficiaries can choose any public or private empanelled hospital they like and request any treatment/therapy identified under the scheme. Additionally, the scheme includes a one year follow up package of cashless services, including consultation, tests, and treatment in the identified follow-up therapies. Also, the scheme distinctively covers the cost of food during treatment and the cost of transportation home post-discharge from the hospital. By 2011-12, the benefit coverage of the scheme was gradually extended to 938 identified treatments, 125 follow-up therapies, and a network of 454 empanelled hospitals, including 98 government and 356 private healthcare providers (Table 8,Table 9). The beneficiaries already covered by other central government health programs[12] are not allowed to demand treatment under Aarogyasri for the treatment procedures covered under those programs.

Other features of the scheme include the organization of health camps to popularize the scheme and the recruitment of 'Aarogya Mithras' (a friend of health) to assist the beneficiaries. Aarogya Mithras work at the help desks of empanelled hospitals, assist the patient from arrival to discharge, and ensure that the patient receives the cash to travel back home post-discharge from the hospital. The basic information about the patient and the entire process, from primary screening to travel compensation, is recorded in an online system to maintain transparency.

[12] CGHS, ESIS, Railways

5 Data

This study uses microdata from the India Human Development Survey for the years 2004-05 and 2011-12. IHDS is a household-level panel survey of 40,000 households, containing 2,00,000 individuals, representing 0.02 percent of the population in India. IHDS is the first large nationwide panel survey documenting the changes in the daily lives of Indian households over time. The survey covers various socio-economic indicators related to education, health, employment, social networks, gender relations, marriage and family structure. The survey has been extensively used in research for over 500 published papers.

The first two rounds of the survey, IHDS I & II, have been jointly organized by researchers from the University of Maryland, USA, and the National Council of Applied Economic Research (NCAER), New Delhi, India and funded by the National Institute of Health (NIH), Maryland. The data for the two rounds is publicly available through the Inter-University Consortium for Political and Social Research (ICPSR). The first round, IHDS-I, includes a nationally representative sample of 41,554 households, containing 215,574 individuals, in 384 districts, 1503 villages, and 971 urban neighbourhoods across 33 states and union territories of India except for Andaman & Nicobar and Lakshadweep. The second round, IHDS-II, covers a sample of 42,152 households in 384 districts, 1420 villages, and 1042 urban neighborhoods across the same region. The 42,152 households interviewed in IHDS-II include 2,134 new replacements due to the inability to locate the former households. This study considers a subsample of only 40,018 households (or 80,036 household-level observations) interviewed in both IHDS-I and II. Excluding the cases of missing and invalid data on dependent and independent variables in both surveys, the final dataset is restricted to household-level 79,772 observations.

Using the survey weights reported in the first round, this study constructs a new weight, *hhweight*, to weigh the household-level observations for all estimations. *hhweight* is generated by interacting $SWEIGHT$ with $NPERSONS04$, i.e., the household weight and household size reported in the 2004-05 round, respectively. *hhweight* imparts more weight to households with a higher number of members.

The measures of educational investment are constructed using the indicators on education-related consumption expenditure of the household. The household-year-specific estimates of the three dependent variables are calculated below:

$$\text{ShareEdu} = \frac{\text{Nominal Annual Education Expenditure} \times \frac{30}{365}}{\text{NPERSONS} \times \text{MPCE}}$$

$$\text{EduExp} = \frac{\text{Nominal Annual Education Expenditure} \times \frac{30}{365}}{\text{NPERSONS}} \times DEFLATOR$$

$$\text{LoanEdu} = \begin{cases} 1, & \text{if a loan has been taken for educational purpose} \\ & \text{by the household in the past five years} \\ 0, & \text{otherwise} \end{cases}$$

where *ShareEdu* is a measure of the share of education in monthly per capita total consumption expenditure of the household. Nominal annual education expenditure is the household's total expenditure on school/college fees, private tuition fees, school books, and other educational articles in the past 365 days. *MPCE* is the monthly total consumption expenditure of the household. *NPERSONS* is the total number of members in the household. *EduExp* is a measure of the household's real monthly per capita education expenditure, adjusted for price changes using the Tendulkar poverty line. *DEFLATOR* is the deflator given in the IHDS-II survey. *DEFLATOR* is based on poverty cut-offs using the Tendulkar method and has been adjusted for interview dates. The value of *DEFLATOR* is one for the year 2004-05, as we consider 2004-05 as the base year. *LoanEdu* is a dummy variable that equals one if the household has taken a loan for educational purposes in the last five years from the survey interview date.

6 Descriptive Statistics

Before moving on to the regression analysis, we establish the plausibility of the hypothesis about Aarogyasri impacting intra-household educational investments by analyzing the change in the averages of dependent variables over time. Let $\bar{Y}^k_{i,PRE}$ and $\bar{Y}^k_{i,POST}$ denote the average value of dependent variable k where i $\{T, C\}$ for treatment and control group before or after Aarogyasri. The analysis inspects whether the change in dependent variable k for Andhra Pradesh differs from that in the control states, i.e. we aim to estimate $[(\bar{Y}^k_{T,POST} - \bar{Y}^k_{T,PRE}) - (\bar{Y}^k_{C,POST} - \bar{Y}^k_{C,PRE})]$.

In the analysis, the treatment group consists of the entire population of Andhra Pradesh, encompassing both those below the poverty line (BPL) and above the poverty line (APL). This choice is based on the fact that by 2011-12, 90% of households in Andhra Pradesh were eligible for Aarogyasri (Table 18). Considering the entire state as the treatment group helps mitigate any potential confounding effects arising from selectivity issues related to ration card holdings, as illustrated in Table 18. Table 18 illustrates that the percentage of households holding BPL ration cards in Andhra Pradesh rose from 87% in 2004-05 to 90% in 2011-12, indicating a 3 percentage point increase. In contrast, other Indian states experienced only a 0.2 percentage point change in the proportion of households holding BPL ration cards. The substantial increase in BPL ration card ownership in Andhra Pradesh suggests that households in the state may have deliberately chosen to hold BPL ration cards to qualify for Aarogyasri. However, it is essential to consider that this increase could also be attributed to the state government's decision to raise the annual income limit for BPL ration cards in 2008[13].

The control group analyzed in this study comprises households from various Indian states, specifically excluding those from confounder states and outliers. Confounder states are defined as Indian states that implemented their own state-sponsored public health insurance programs between 2004-05 and 2011-12, such as Tamil Nadu, Maharashtra, Gujarat, Kerala, Karnataka, and West Bengal. Outliers include

[13] In 2008, the government of Andhra Pradesh increased the annual income limit for white ration cards from 20,000 to 60,000 Indian rupees per annum in rural areas and from 24,000 to 75,000 Indian rupees in urban areas. Source:https://economictimes.indiatimes.com/news/economy/policy/ap-to-bring-more-people-under-bpl-category-of-ration-cards/articleshow/3175836.cms (accessed on October 3, 2022)

households from states with small populations, such as Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Assam, and Goa. Additionally, households from India's union territories are also considered outliers. Therefore, the control group, referred to as control states, includes households from Jammu and Kashmir, Himachal Pradesh, Punjab, Uttarakhand, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Odisha, and Chhattisgarh. The graphical representation of the treatment and control groups is depicted in Figure 8.

Table 15 provides a comprehensive summary of the averages concerning educational investments across various years and treatment groups. In each panel, Rows 1 and 2 delineate the averages for households in rural and urban areas, respectively. Row 3 of each panel presents the overall average for both rural and urban regions. Columns (A) and (C) represent the averages before the implementation of Aarogyasri, whereas columns (B) and (D) showcase the averages after the introduction of Aarogyasri. Column (B-A) computes the value $(\bar{Y}^k_{T,POST} - \bar{Y}^k_{T,PRE})$ for variable k, while column (D-C) calculates $(\bar{Y}^k_{C,POST} - \bar{Y}^k_{C,PRE})$. The disparity between columns (B-A) and (D-C), denoted as (B-A)-(D-C), quantifies the variation in the increase between Andhra Pradesh and the control states, represented as $\left[(\bar{Y}^k_{T,POST} - \bar{Y}^k_{T,PRE}) - (\bar{Y}^k_{C,POST} - \bar{Y}^k_{C,PRE})\right]$. Notably, column [(B-A)-(D-C)] underscores that the rise in the average share of education in total expenditure is 0.2 percentage points higher in Andhra Pradesh compared to the control states. Similarly, in column [(B-A)-(D-C)], Andhra Pradesh exhibits a greater increase in the average real education expenditure by 19.6 Indian rupees and a 4-percentage-point rise in the proportion of households obtaining education loans.

Table 16 extends our analysis by presenting averages similar to those in Table 15, focusing specifically on APL (Above Poverty Line) and BPL (Below Poverty Line) households separately. For the BPL category, our sample is limited to the most impoverished households falling below the 80th percentile of real monthly per capita consumption expenditure. Column [(C-A)-(G-E)] highlights the contrast between the pre and post Aarogyasri changes in averages for APL households in Andhra Pradesh and the control states. Similarly, column [(D-B)-(H-F)] illustrates the difference for BPL households. Notably, column [(D-B)-(H-F)] indicates that the increase in the average share of education for BPL households is higher in Andhra Pradesh by 0.3 percentage points. Conversely, column [(C-A)-(G-E)] reveals that the change in the average share of education for APL households is 5 percentage points lower in Andhra Pradesh. The analysis of APL households is crucial, as these households are ineligible to avail Aarogyasri benefits. Therefore, the disparities in averages for APL households signify the pre-existing differences in the sample, unrelated to the impact of Aarogyasri, representing the inherent heterogeneity effect. To isolate the effect of Aarogyasri on BPL households, we calculate the triple difference, denoted as

$$\Big[(\bar{Y}^k_{T,POST,BPL} - \bar{Y}^k_{T,PRE,BPL}) - (\bar{Y}^k_{T,POST,APL} - \bar{Y}^k_{T,PRE,APL})\Big]$$
$$- \Big[(\bar{Y}^k_{C,POST,BPL} - \bar{Y}^k_{C,PRE,BPL}) - (\bar{Y}^k_{C,POST,APL} - \bar{Y}^k_{C,PRE,APL})\Big]$$

Consequently, the net average effect of Aarogyasri on the share of education for BPL households in Andhra Pradesh is 5.3 percentage points, providing robust support for our hypothesis. Furthermore, the net average effect of Aarogyasri on real education expenditure for BPL households and the proportion of BPL households resorting to education loans stands at 36.9 percentage points and -5 percentage points, respectively.

Next, we shift our focus to a comparison of monthly averages, seasonally adjusted, between Andhra Pradesh and the control states both before and after the implementation of Aarogyasri. Our visualization of these monthly averages, along with their linear trends, is presented in Figure 2, Figure 3, and Figure 4 (for detailed information on the construction of these graphs, please refer to Section 7.1). Figure 2 illustrates that prior to 2007, the trend in the growth of monthly averages for the share of education was remarkably similar between Andhra Pradesh and the control states. However, following 2007, these trends began to diverge, with the monthly average for the share of education experiencing a more pronounced increase in Andhra Pradesh compared to the control states. This visual discrepancy suggests a noteworthy post-2007 impact of Aarogyasri on the growth of the share of education in monthly expenditure. This outcome is mirrored in Figure 3 and Figure 4, which demonstrates the real education expenditure and the probability of taking education loans. After 2007, the real education expenditure and the proportion of households in Andhra Pradesh accessing education loans demonstrate a more pronounced upward trajectory compared to the control states. Upon narrowing our focus to

BPL households exclusively, Figure 5, Figure 6, and Figure 7 provide further insights. These figures reveal that, among BPL households, after 2007, the monthly averages for all three dependent variables experienced a notably higher rate of growth in Andhra Pradesh as compared to the BPL households in the control states. This divergence underscores the unique impact of Aarogyasri on BPL households.

The descriptive statistics provide compelling evidence that Aarogyasri resulted in a differential change in educational investments for Andhra Pradesh, supporting the plausibility of the paper's hypothesis. However, it is crucial to note that the descriptive statistics tables merely present simple averages and do not account for the influence of other factors. To address this limitation and take into consideration the potential effects of other variables, we transition to a more comprehensive regression analysis.

7 Identification Strategy

7.1 Identifying Assumptions

In the context of a Difference-in-Differences (DID) model, the validity of the obtained results hinges upon specific underlying assumptions. This discussion critically assesses the applicability of these assumptions in the present study. If these assumptions are found to be invalid, the focus then shifts to devising an identification strategy capable of mitigating the bias introduced by these assumptions in the DID estimate.

For the DID strategy to deliver consistent and unbiased estimates, the first assumption that must hold is that the households in Andhra Pradesh and the control states were reasonably similar before the implementation of Aarogyasri. To validate this assumption, we examine the balance of covariates between households in Andhra Pradesh and the control states before the introduction of Aarogyasri. Table 17 provides a comprehensive overview of household-level covariates related to demographic characteristics, health status of household members, healthcare financing, and assets. These covariates are categorized by year and treatment group, with columns (A)-(D) displaying their respective averages. Column (A-C) illustrates the disparity in covariate averages between Andhra Pradesh and the control states prior to Aarogyasri's launch, while column (E) reports the associated p-value. If the p-value is less than 0.01 during the pre-period, it signifies a significant difference between households in Andhra Pradesh and the control states at the 1 percent level of significance. The analysis in Columns (A-C) and (E) demonstrates that before the implementation of Aarogyasri, households in Andhra Pradesh significantly differed from those in the control states concerning 15 out of 18 covariates. Furthermore, Columns [(B-A)-(D-C)] and (F) indicate a significant difference between Andhra Pradesh and the control states in the change in covariate averages over time for 14 out of 18 covariates. These disparities persist even after employing within-group transformations of variables or fixed effects, indicating the potential for bias in the DID estimate originating from these 14 covariates. To mitigate this concern, we control for these 14 covariates in the regression analysis.

The second assumption is that the educational investments in control states are unaffected by the introduction of Aarogyasri in Andhra Pradesh, commonly known as the SUTVA assumption. The assumption is violated if there are spillover effects of Aarogyasri from Andhra Pradesh to the control states. One source of spillover effects could be migration. If Aarogyasri causes the households in Andhra Pradesh to migrate to the control states, then the estimated DID effect might underestimate the true effect of Aarogyasri. Otherwise, if Aarogyasri causes the households in control states to migrate to Andhra Pradesh, then the estimated DID effect might overestimate the true effect of Aarogyasri. Alternatively, spillovers could arise from contact between the households in control states and the non-resident household members from the households in Andhra Pradesh residing in control states or vice versa. To check if there could be a possibility of spillover effects from migration, we estimate the percentage of the population from other Indian states migrating to Andhra Pradesh in Table 12 using the data from 1991, 2001, and 2011 Census of India. Using the information in the 1991 and 2001 Census on migrated households residing in Andhra Pradesh for more than ten years, we estimate the proportion of population from other Indian states migrating to Andhra Pradesh before 2001 in column (A). Similarly, using the information in the 2011 Census on migrated households residing in Andhra Pradesh for between 5 and 9 years, we estimate the proportion of population from other Indian states migrating to Andhra Pradesh between 2001 and 2006 in column (B). Again, using the information in the 2011 Census on migrated households residing in Andhra Pradesh for between 1 and 4 years, we estimate the proportion of population from other Indian states migrating to Andhra Pradesh between 2006 and 2011 in column (C). We divide other Indian states into four sets, and the rows in each column represent the population migrating from the states in the respective set. Comparing rows 1 and 4 in column (C), we find that the percentage of the population migrating with their household from control states to Andhra Pradesh post Aarogyasri is the same as the percentage of the population migrating from non-neighbouring (not sharing border with Andhra) confounder states. Also, comparing rows 1 and 3 in column (C), we find that migration to Andhra Pradesh from the control states is lower than the migration to Andhra Pradesh from non-south Indian confounder states. As the households in confounder states already have access to their state's health insurance schemes, this indicates that the interstate migration to Andhra Pradesh after Aarogyasri might be happening due to factors other than public health insurance. Hence, we assume that the SUTVA assumption is likely to be upheld in this study.

The third assumption is the monotonicity/ no-defiers assumption. It assumes that the households in control states always remain untreated and the households in Andhra Pradesh do not switch back from being treated to untreated. The assumption holds in this study, firstly, because we exclude the states that launched their own state-sponsored health insurance scheme between 2004-05 to 2011-12 from the control group in the experimental design. So, the control group remains untreated in the time period considered for the study. The latter part of the assumption is valid, firstly, as per the institutional setting of Aarogyasri. Once Aarogyasri is launched in a district in Andhra Pradesh, there is no reversal until 2011-12. Secondly, a household in Andhra Pradesh would be a defier if it chooses to migrate to other Indian states or countries to become ineligible for Aarogyasri. However, there is no reason to believe that the scheme is forcing households to migrate from Andhra Pradesh to other Indian states or countries. Households in Andhra Pradesh have the choice to not participate in the scheme for any reason, such as no illness, travel constraints to the nearest empanelled hospital, required therapy being uncovered, etc.

The fourth assumption is parallel trends in the pre Aarogyasri period. The assumption implies that before Aarogyasri was launched in 2007, educational investments were growing similarly between

Andhra Pradesh and the control states. The assumption is valid in this study if the temporal changes in educational investment outcomes are parallel between Andhra Pradesh and the control states before Aarogyasri. However, with no data available for the years before 2004-05 and the years after 2011-12, to plot parallel trends, we use monthly averages of the dependent variables over the period November 2004-October 2005 and January 2011-March 2013. To elaborate further, the data collection under the IHDS survey for a particular state continued for multiple months. For example, if we observe Andhra Pradesh, the data collection was completed over nine months between December 2004 and October 2005. Accordingly, we get nine data points for Andhra Pradesh. We exploit the variation in the growth of household variables over time to plot the graphs. We assume that the interview dates for households within a state were assigned randomly. Further, to deseasonalize the data, we run the regression below separately for Andhra Pradesh and the control states for each year and each outcome variable, i.e. we run the regression for 2 × 2 × 3 sets.

$$y_i = \beta_0 + \sum_{k=2}^{12} \beta_{k1}.dtime_k + \beta_2.mpcepl_i + \epsilon_i \tag{7}$$

Here, y_i is the outcome variable on educational investment for household i. To remove the effect of seasonality, we add month dummy $dtime_k$ for month k. $mpcepl_i$ is real monthly per capita consumption expenditure of household i, deflated as per Tendulkar's poverty line. To save degrees of freedom, instead of using state fixed effects, we chose to add this variable to control for any state-specific effect related to per capita income or GDP. Regression is weighted using *hhweight*. After running the regression, we obtain an estimate of $\hat{y}_i$ and error predictions, $\hat{\epsilon}_i = y_i - \hat{y}_i$. $\hat{\epsilon}_i$ represents the deseasonalized value of variable y_i. We plot $\hat{\epsilon}_i$ against months on the x-axis and fit a linear trend over the data points for deseasonalized monthly averages. Figure 2, Figure 3, and Figure 4 illustrate the linear trends in educational investment outcomes graphically. We repeat the same process after restricting the sample to BPL households to observe the linear trends in outcome variables for only BPL households in Figure 5, Figure 6, and Figure 7. Though before 2007, the trends appear parallel visually, we test for the hypothesis that the slopes of pre-trends for Andhra Pradesh and the control states in Figure 2-Figure 7 are equal. We run the regression below for each educational investment outcome:

$$\hat{\epsilon}_i = \beta_0 + \beta_1 time + \beta_2 1[AP]_i + \beta_3 1[AP]_i \times time + \varepsilon_i \tag{8}$$

where $\hat{\epsilon}_i$ is deseasonalized value of the outcome variable for household i, $1[AP]$ is Andhra Pradesh dummy and ε_i is error term. *time* is the number of months since the survey began in November 2004 till the date of the interview for household i. β_3 represents the differential in slope of the linear trend in $\hat{\epsilon}_i$ for Andhra Pradesh. Based on the results presented in Table 19, β_3 is insignificant at a five percent level of significance, for all six regressions. That is, we fail to reject the null hypothesis that the slopes are equal for the period 2004-05 at a five percent significance level. Hence, evidence supports the parallel trends assumption.

The fifth is the unconfoundedness assumption which assumes that all the relevant factors influencing Andhra Pradesh, control states, and Aarogyasri are observed and can be controlled for. If not, then no unobserved shocks occurring between 2004-05 and 2011-12 should affect the educational investments in Andhra Pradesh and the control states differently. To address this concern, we sort the unobserved factors that might have a direct effect on educational investments in three categories; (i) time-invariant factors, existing before November 2004, (ii) time-invariant factors, occurring from November 2004 till March 2013 and beyond, and, (iii) time-variant factors. As the common trends assumption is satisfied in this study, the trend in the differential effect of unobserved factors existing in the pre-period on the educational investments in Andhra Pradesh and the control states is constant and gets eliminated by DID. The effect of category (ii) of unobserved factors is eliminated by within transformation of variables in the regression estimations. Regarding category (iii) of unobserved factors, we list the shocks occurring between November 2004 and March 2013 in Table 14.

Table 14 summarises the potential confounders, the potential bias arising from them in the casual estimate of Aarogyasri, and the identification strategy, if any, to subdue their bias on the causal impact of Aarogyasri. The experimental design has already discussed the first two confounders in detail - the selectivity issue in BPL ration card holding by the households in Andhra Pradesh and the introduction of state-sponsored health insurance programmes in other Indian states between 2004-05 and 2011-12.

The strategy of keeping all households in Andhra Pradesh in the treatment group instead of just the BPL households subdues any confounding effect from selection into treatment. Besides, we exclude the confounder states from the control group. The third potential confounding effect arises from the impact of loans taken from any source to fund education. We, thus, consider a variable on education loan, $LoanEdu$, as one of the educational investment outcome variables and estimate the system of regression equations with the three dependent variables simultaneously using the Seemingly Unrelated Regression method. The fourth potential confounder is the Direct Benefit Transfer (DBT) educational scholarship provided by the Andhra Pradesh government. The scholarship provides cash transfers to poor households to fund their children's education. In the IHDS survey, any cash transfer received by the household forms a part of the household's total consumption expenditure. Hence, controlling for the monthly per capita consumption expenditure in the regression automatically controls for the DBT scholarship. Next is the introduction of central government health insurance schemes between 2004-05 and 2011-12, such as the Rashtriya Swasthya Bima Yojana (2007) and the Aam Aadmi Bima Yojana (2007). Only if the extent of coverage of central government schemes varies between Andhra Pradesh and the control states, the effect of these schemes on educational investments will differ between the treatment and the control groups and will not be eliminated by DID. In such a situation, a reduction in the price of health is created jointly by Aarogyasri and the central schemes, overestimating the effect of Aarogyasri. We discuss the impact of the central schemes and the other changes happening in Andhra Pradesh between 2004-05 and 2011-12, which are likely to impact educational investments, such as the Microfinance crisis (2010), Jawahar Bal Aarogya Raksha Yojana (2010), and rise in the number of school or college going individuals in the robustness checks section.

7.2 Estimation

The goal of this paper is to estimate the following reduced-form equations:

$$\begin{aligned} ShareEdu_{it} = {} & \alpha_1^s.1[Year2011]_t + \alpha_2^s.1[AP]_{it} + \alpha_3^s.1[Year2011]_t \times 1[AP]_{it} \\ & + \alpha_4^s.\Gamma_{it} + \alpha_5^s.\Omega_{it} + \lambda_i + \epsilon_{it}^s \end{aligned} \tag{9}$$

$$MpcEdu_{it} = \alpha_1^m.1[Year2011]_t + \alpha_2^m.1[AP]_{it} + \alpha_3^m.1[Year2011]_t \times 1[AP]_{it}$$
$$+ \alpha_4^m.\Gamma_{it} + \zeta_i + \epsilon_{it}^m \tag{10}$$

$$LoanEdu_{it} = \alpha_1^l.1[Year2011]_t + \alpha_2^l.1[AP]_{it} + \alpha_3^l.1[Year2011]_t \times 1[AP]_{it}$$
$$+ \alpha_4^l.\Gamma_{it} + \alpha_5^l.\delta_{it} + \psi_i + \epsilon_{it}^l \tag{11}$$

where $ShareEdu_{it}$ is the share of education in monthly per capita consumption expenditure of household i in time t. $MpcEdu_{it}$ is the real monthly per capita education expenditure of the household i in time t. $LoanEdu_{it}$ is a dummy variable equal to 1 if household i has taken a loan for educational purposes in the past five years from the date of the survey in time t.

Amongst the independent variables, $Year2011$ is a dummy variable equal to 1 if the observation i was recorded in the year 2011-12 and AP is a dummy variable equal to 1 if the household i resides in the state of Andhra Pradesh. $Year2011$ controls for time fixed effects, i.e., heterogeneity in intra-household educational investments by time, caused by varying economic conditions from the baseline year to the next year or the variation in publicization of the Aarogyasree scheme across time. λ_i, ζ_i and ψ_i control for household fixed effects. Γ_{it} comprises time-varying household characteristics that could directly affect educational investments such as household size, rural/urban location, gender of household head, education of household head, monthly per capita consumption expenditure, caste, and occupational status of household members. Ω_{it} comprises variables related to household members' health such as the number of household members seeking medical treatment in the past year. δ_{it} comprises variables related to household assets that could constrain a household's borrowing capacity such as house ownership, land holding, and ownership of durable goods. ϵ_{it}^1, ϵ_{it}^2 and ϵ_{it}^3 indicate the error terms comprising all omitted variables.

The coefficient of interest is α_3^k, $k \quad \{s, m, l\}$, which captures the relationship between the dependent variable on educational investment and the interaction between year and Andhra Pradesh dummy variable. Basically, α_3^k represents the DID $[(\bar{Y}_{T,POST}^k - \bar{Y}_{T,PRE}^k) - (\bar{Y}_{C,POST}^k - \bar{Y}_{C,PRE}^k)]$, i.e. the effect of

Aarogyari. A positive coefficient would be consistent with the effect hypothesized. All other coefficients in the specification capture the temporal changes in educational investments across households in all states for reasons not specific to Andhra Pradesh.

All things considered, we eliminate the household fixed effects in the regression by exploiting the panel data structure of the IHDS dataset to perform a within transformation of the variables[14]. The within transformation allows us to avoid making an additional assumption about the distribution of time constant household characteristics and improves efficiency (see subsection 10.1 for proof). For every variable X_{it} in the system of equations above, we take the time average of household i for variable X and calculate the variation of household i about the household-specific time average for variable X. Mathematically, the within transformation of variable X_{it} is given by

$$X_{it}^{wd} = X_{it} - \frac{\sum_t^T X_{it}}{T} \tag{12}$$

where T is the total number of time periods. Here, $T = 2$. Thereby, we obtain the following system of equations:

$$ShareEdu_{it}^{wd} = \beta_1^s.1[Year2011]_t^{wd} + \beta_2^s.(1[Year2011]_t \times 1[AP]_{it})^{wd} + \beta_3^s.\Gamma_{it}^{wd} + \beta_4^s.\Omega_{it}^{wd} + \epsilon_{it}^{swd} \tag{13}$$

$$MpcEdu_{it}^{wd} = \beta_1^m.1[Year2011]_t^{wd} + \beta_2^m.(1[Year2011]_t \times 1[AP]_{it})^{wd} + \beta_3^m.\Gamma_{it}^{wd} + \epsilon_{it}^{mwd} \tag{14}$$

$$LoanEdu_{it}^{wd} = \beta_1^l.1[Year2011]_t^{wd} + \beta_2^l.(1[Year2011]_t \times 1[AP]_{it})^{wd} + \beta_3^l.\Gamma_{it}^{wd} + \beta_4^l.\delta_{it}^{wd} + \epsilon_{it}^{lwd} \tag{15}$$

We expect the error terms across the three equations to be correlated as similar omitted variables are likely to influence all three educational investment-related outcome variables. We check for

[14]Rather than within transformation, we could have directly controlled for fixed effects while estimating the regression in Stata. But, we estimate these equations further using the SUR method, and the 'sureg' command in STATA version 16.1 doesn't provide an option to adjust for unit fixed effects. Source: https://www.stata.com/manuals/rsureg.pdf

cross-equation dependence by estimating the variance-covariance matrix of error terms after running OLS regression and predicting error terms $\hat{\epsilon^k_{it}}$. Table 11 presents the variance-covariance matrix of error terms after running OLS regression on Equation 13-Equation 15. The table shows that there is a high correlation between errors $\hat{\epsilon^s}$ and $\hat{\epsilon^m}$. To deal with this issue, we estimate the above system of Equation 13-Equation 15 simultaneously using the Seemingly Unrelated Regression (SUR) method to adjust for the non-independence of errors across the three equations. Adjusting for cross-equation dependence improves efficiency. Standard errors are adjusted for heteroskedasticity by using robust standard errors. Regression is weighted using household weight *hhweight* to adjust for the non-randomness in the selection of households in the sample.

8 Results

8.1 Main results

Results strongly confirm theoretical predictions. Education expenditures, education expenditures as a percentage of total household expenditures, and the probability of taking educational loans have all increased since the introduction of Aarogyasri in Andhra Pradesh. Furthermore, all of the estimated effects are statistically and economically significant.

Row 1 in Table 1 shows that, on average, Aarogyasri's implementation increases per capita educational expenditure by 11.4 Indian rupees (constant prices in 2004-05), when all other factors are maintained constant. This represents a 39 percent increase over the average private education expenditure of 29.6 Indian rupees during 2004-05. In real terms, this amounts to an increase of 11,363 million Indian rupees in expenditures by private households due to Aarogyasri. It is substantial by any standard.

The introduction of Aarogyasri also raises the share of household expenditures on education. It can be seen from Row 1 in Table 1 that, on average, the share of educational expenditures in the total household budget increases by 0.0031 or by 0.31 percentage points. This indicates an increase of 10 percent in educational expenditures over the 3 percent in 2004-05. Needless to say, the introduction of Aarogyasri enhances the relative importance of education in households' consumption profile.

Educational loans may also contribute to an increase in educational expenditures. Individuals with limited resources may also take out loans to cover the cost of their educational expenses. The results suggest that Aarogyasri has increased the likelihood of households taking out loans for educational purposes. Row 1 in Table 1 indicates that Aarogyasri increases the probability of taking out an education loan by 3.7 percentage points. It represents a significant increase of 185 percent in the likelihood of taking out an educational loan. By any standard, this represents a significant improvement.

8.2 Disentanglement between Price and Human Capital Investment Effects

We disentangle the impact of human capital investment from the price effect of Aarogyasri by introducing a control variable representing the overall life expectancy of households. Utilizing the dataset encompassing age-wise life expectancy statistics pertaining to various Indian states, as provided by the Center for Monitoring Indian Economy (CMIE), we undertake the construction of variable $LifeExp_{it}$, representing the life expectancy of household i at time t. A higher value of $LifeExp_{it}$ signifies prolonged survival among household members.

Let LE_{ksrat} denote the life expectancy measure of individual k in age stratum a, residing in Indian state s and sector r (rural or urban), at time t. The composite life expectancy metric corresponding to household i at time t can be ascertained as the cumulative sum of the individual life expectancies applicable to all constituent members of the household at time t.

$$LifeExp_{it} = \sum_{k=1}^{N} LE_{ksrat} \tag{16}$$

where N is the size of household i at time t.

We incorporate the variable $LifeExp$, and its interactions with the year and treatment dummy, in the benchmark Equation 9-Equation 11. Theories on human capital investments indicate that longer life expectancy encourages households to invest more in education as they are more likely to see the benefits of education paying off over a longer span of time (Ben-Porath 1967). Accordingly, controlling for $LifeExp$ segregates the human capital investment effect from the DID effect of the treatment (Aarogyasri). The coefficient of the interaction term $Year2011 \times AP$, then, represents the price effect of Aarogyasri.

Row 1 of Table 3 shows that the price effect of Aarogyasri on education expenditures is 1.3 Indian rupees, which is one-tenth of the total effect in the benchmark regression. In contrast, the price effect on the probability of taking a loan is large, with 2.7 percentage points forming about 70 percent of the total effect. Interestingly, the price effect of Aarogyasri on the share of household expenditures on education is negative, indicating strong evidence for the presence of a large and positive human capital investment effect.

8.3 Robustness Checks

In the sections on data and estimation, we discuss the rationale for selecting the specification and subsample. However, to verify the robustness of the results, we reran the analysis with different subsamples and specifications. Estimates from this robustness exercise support the qualitative results, indicating that the results are invariant to a variety of specifications and datasets.

The benchmark regression above (results shown in Row 1 of Table 1) excludes some of the smaller states. Some of these states are from the north-eastern part of the country and others are the union territories. Consequently, these states generally have different administrative structures, are prone to political instability, or lack administrative autonomy when it comes to making decisions that affect outcomes, such as education investments. In addition, political instability and limited administrative freedom can make these states less likely to offer health insurance to their citizens. Therefore, this exclusion may lead to a confounding of the results. As a test of whether the results are still valid in the presence of these states, we replicated the regression, taking them into account.

The inclusion of these states did not significantly alter the results. Row 2 of Table 1 indicates that education expenditures increased by 10.4 Indian rupees while the share of educational expenditures and probability of taking out educational loans increased by 0.32 and 3.7 percentage points, respectively. Clearly, these results are very similar to those reported in the benchmark regressions (Row 1 of Table 1), indicating that the differences in administrative structures and constraints will not affect the results.

Health services delivery is another important aspect of health care. At a mass level, it is dependent on the administrative infrastructure of the states. Providing effective healthcare services in a large state is significantly more challenging than doing so in a smaller one. In order to avoid this component as well as other time-invariant heterogeneities, we employ a fixed effect model. To ensure that the size of the state does not further influence the results, we reran the benchmark specifications using only large population states such as Uttar Pradesh, Bihar, Madhya Pradesh and Rajasthan as controls. Results remain largely unchanged. As shown in Row 3 of Table 1, educational expenditures increased by approximately 40 percent or 15.7 Indian rupees. The probability of taking a loan remains unchanged at 3.7 percent. In contrast, the share of education decreases by 0.17 percentage points, which is almost half of what is found in the benchmark specification (Row 1 of Table 1). It is interesting to note that even though there is a large jump in actual expenditures in Aarogyasri, there is a smaller increase in the share of educational expenditures.

A major concern for this estimation is that a policy such as Aarogyasri may attract individuals from other states. If this cross-state migration brings individuals who are also more likely to spend more on education, one would expect to see a greater effect on educational investments. This constitutes a violation of the SUTVA. For this purpose, we consider Orissa and Chhatisgarh, neighboring states, to be the control states. Row 4 of Table 1 reports the results. We find some evidence of SUTVA violations. The estimated effects are stronger for two of the three outcome variables. Education expenditures increased by 19 Indian rupees and the expenditure share increased by 4.4 percentage points. It is approximately 75 percent and 40 percent higher than the benchmark models' educational expenditure and share of expenditure estimates, respectively. However, the effects on loan taking remain the same. Thus, it is possible that a population from Orissa and Chhatisgarh migrated to Andhra Pradesh in order to take advantage of the policy. After examining this matter in detail, we find that these violations will not have a significant impact on the benchmark estimates.

In order to determine whether this apparent violation of the SUTVA may influence our results, we exclude Orissa and Chhatisgarh, bordering states, and consider only states not sharing borders with Andhra Pradesh as control states. Using this method yields similar results. Row 5 of Table 1 shows that education expenditure has increased by 11 Indian rupees, while educational expenditure share and probability of educational loan taking have risen respectively by 0.30 and 3.7 percentage points. Considering that the results are almost identical to those from the benchmark specifications, Orissa's and Chharisgarh's inclusion was not confounding the results due to possible SUTVA violations. Possibly there are two reasons for this invariance. Firstly, it may be because Orissa and Chhatisgarh are relatively smaller than the total number of states. Secondly, if states do not share common borders, interstate migration is relatively costly.

Another way to determine whether Aarogyasri has caused the changes in educational investment or whether other factors have contributed to these changes is to compare Andhra Pradesh with other states that have introduced similar health insurance plans in a similar timeframe. If the effects diminish significantly as compared to the benchmark results, one may reasonably conclude that Aarogyasri was responsible for altering educational investments. However, if Andhra Pradesh continues to show the effect, it might be considered that other factors may have contributed to the change. Incidentally, Andhra Pradesh and these control states are mostly southern states with similar socio-cultural and socio-economic characteristics. Row 7 of Table 1 shows the share of educational expenditures remains unchanged at 0.3 percentage points. In contrast, education expenditures and the probability of taking out loans have declined significantly by more than 100 and 35 percent, respectively. Hence, the impact of Aarogyasri was indeed due to health insurance and not to the other concomitant factors that changed in Andhra Pradesh from 2004-05 to 2011-12.

Another major concern with this estimation is that the main results might represent the joint effect of Aarogyasri and Rashtriya Swasthya Bima Yojana (RSBY). RSBY is a popular central government health insurance scheme launched across India in 2007. Much like Aarogyasri, RSBY provides cashless treatment to beneficiaries at the hospitals empanelled under the scheme. However, availing treatment under RSBY requires that the beneficiary holds a smart card issued by the government with an annual registration/renewal fee of 30 Indian rupees per annum. Besides, RSBY provides coverage only up to 30,000 Indian rupees annually and is restricted to five family members[15], while Aarogyasri provides coverage of 2 lakh Indian rupees with no restrictions on the number of family members. Despite high transaction costs and low financial coverage under RSBY, we observe in our data that the incidence of smart cards is much higher in Andhra Pradesh as compared to the control states. In 2011-12, 83.6 percent of the households in Andhra Pradesh reported having RSBY smart cards as compared to only 15.5 percent in the control states. Thus, we expect that the main results represent the joint effect of Aarogyasri and RSBY. We attempt to segregate the impact of RSBY and Aarogyasri by constructing a dummy variable $RSBY_i$ equal to 1 if household i reports holding a Rashtriya Swasthya Bima Yojana smart card in the IHDS-II survey, and zero otherwise. We include $RSBY$ and its interactions with the year and treatment dummies in our benchmark Equation 9-Equation 11. The coefficient of the interaction term $RSBY \times Year2011 \times AP$ captures the differential effect of RSBY on households in Andhra Pradesh holding an RSBY smart card. Clearly, Table 4 provides evidence that the differential effect of RSBY on households in Andhra Pradesh is insignificant. Hence, we conclude that the effect of RSBY is eliminated by the DID estimation strategy. Even if RSBY has any effect, the argument that health coverage positively influences educational investments remains valid.

An alternate potential confounder could be the Jawahar Bal Aarogya Raksha Yojana (JBARY) launched by the state government of Andhra Pradesh in 2010. JBARY provides nutritious food and health treatment free of cost to children in government schools. Hence, JBARY is likely to improve the health of children going to government schools and expand the household budget by reducing medical and food expenses, thus, creating a positive bias in the DID estimate of Aarogyasri. However, as JBARY was introduced on 14th November 2010, while the households in Andhra Pradesh were interviewed for IHDS-II between January and October 2011, JBARY didn't have enough time to spread by the time the IHDS-II survey was completed. Nevertheless, we examine the effect of Aarogyasri on households that are ineligible for JBARY. These are the households where no school-going member attends a government

[15] Source:https://www.india.gov.in/spotlight/rashtriya-swasthya-bima-yojana#rsby4 (accessed on February 28, 2023)

school. We restrict the sample to households where all school-going members attend private schools and rerun our benchmark regressions Equation 13-Equation 15. Row 3 of Table 2 shows that the impact on education expenditures for this subsample of households is more than double the benchmark results (Row 1 of Table 1). The result for the share of education is also higher, while the probability of taking a loan is the same. This implies that JBARY is unlikely to overestimate the effect of Aarogyasri.

Around the time Arogyasri was being implemented across Andhra Pradesh, another significant event took place - the microfinance crisis (2010). This was a major repayment crisis in the Indian microfinance industry. The crisis paralyzed the supply of microfinance loans in India and had a considerable impact on the borrowing capacity of the poor. The crisis primarily impacted the states with a high concentration of microfinance clients in their population, including Andhra Pradesh (1.5%), Karnataka (0.6%), Tamil Nadu (0.9%), West Bengal (0.6%) and Orissa (0.8%)[16]. To eliminate the confounding effect of the crisis in DID, we compare Andhra Pradesh with Orissa. Orissa is the only state amongst the benchmark control states that was highly affected by the microfinance crisis. The results in Row 6 of Table 1 indicate that the effect on the probability of taking a loan remains unchanged as compared to the benchmark results (Row 1 of Table 1). Education expenditure is higher and positive, but statistically insignificant. The share of education has diminished by more than half. It's important to note that the low effect on the share of education could also be due to a small sample size or other changes happening around the same period in Orissa.

The rise in educational investments in Andhra Pradesh could also be due to a rise in the number of people attending school or college in Andhra Pradesh between 2004-05 and 2011-12. We include additional control variables on the number of household members attending school or college, the number of household members attending private school, and the number of household members below 24 years of age (school or college going age), in our benchmark regression Equation 9-Equation 11. The results subsequent to adding these controls are reported in Row 2-4 of Table 3. The results show that the effect on education expenditures and the share of education is higher than the benchmark results, while the effect on the probability of taking a loan is robust to adding these controls.

[16]Data from Table 1.4 in Srinivasan, N. (2010). Microfinance India: State of the sector report 2009. SAGE Publications India.

8.4 Heterogeneity

8.4.1 Effect on households with school/college going children

Although Aarogyasri is practically available to the entire population of Andhra Pradesh, it may have different effects on various subgroups. For example, Aarogyasri may not affect the educational investments of households without children in school or college. On the contrary, one would expect to see a greater effect on educational expenditures for households with children attending school or college. As a check for this heterogeneity, we run three sets of regressions on three separate subsamples. The first subsample consists of households with at least one member attending school or college at the time of the survey. The second subsample consists of households with at least one member under the age of 18. This is primarily to determine whether anyone in the household is of school-going age. A second subsample includes households with at least one member in school or college-going age (age less than 24). It should be noted that the second subsample is a superset of the first, while the third is a superset of the second.

Row 2, 4, and 5 of Table 2 present the results. As expected, the effects are either similar or greater than those of the benchmark regressions. For households with at least one member below 18 years of age, the educational expenditures increased by 13 Indian rupees. Share of educational expenditures and loan taking probabilities rise by 0.67 and 4.3 percentage points, respectively. As a result, the impact on households where educational investment is important is much greater than the impact on other households. Similar results are reported for households with school or college going members and for households with at least one member under the age of 24.

8.4.2 Effect on households below poverty line

An important concern would be how Aarogyasri impacts households below the poverty line. Educating this group is of the utmost importance. Studies show that poor people are more affected by such health insurance than non-poor people. Therefore, if that is indeed the case, then the increase in educational expenditures associated with the newly introduced health insurance coverage would increase the most for the poorest groups. In order to test this hypothesis, the same specification was rerun exclusively for BPL households.

According to Row 1 of Table 2, Aarogyasri increases education expenditures by 18 Indian rupees among the poor, on average. It is approximately 80 percent higher than the overall increase in educational expenditures. The share of education expenditures increases by 0.58 percentage points, which is almost double the average nationwide increase. Nevertheless, the probability of taking out an educational loan has risen by 3.4 percent, similar to the all-Andhra (APL+BPL) increase. These results are consistent with the theoretical predictions.

8.5 Placebo Checks

Based on the above results, it is evident that the results remain unchanged despite the use of different specifications and subsamples of data. To further enhance credibility, we conducted placebo tests to determine whether the positive effect of Andhra Pradesh is unique to Andhra Pradesh or whether other states also experience similar results. In order to achieve this, we perform pairwise placebo tests. We designate each control state as a placebo treatment state and other control states as control states. As previously mentioned, the control group is composed of 13 states. As part of the procedure, each of these 13 states is assigned the role of a placebo treatment state, and the other 12 states are assigned the role of control states. This results in 13 separate regression analyses, one for each case. In none of these regressions, Andhra Pradesh is involved.

Table 20 shows that across all 13 regressions, none shows a statistically significant increase in all three aspects of educational investments. Consequently, no state has shown a systematic increase in these outcome variables between 2004-05 and 2011-12. In 5 of the 13 regressions, only educational expenditures have increased. In 5 of the 13 regressions, the share of expenditure has only increased. None of the 13 regressions indicate an increase in the probability of taking out a loan of more than 0.1 percentage points. In only 4 of the 13 regressions, two out of three outcome variables have shown an increase in the period between 2004/05 and 2011/12. As such, unlike Andra Pradesh, no other state has seen a rise in all three measures of educational investment.

9 Conclusion

Health coverage has complementary effects on educational investments, but they are often overlooked. We examine this issue systematically using a health insurance scheme (Rajiv Arogyashree Health Insurance Scheme, or Aarogyasri) implemented in the Indian state of Andhra Pradesh in 2007/08. Based on a modified difference-in-differences model, we find that Aarogyasri increases educational expenditures by 39 percent, share of educational expenditures by 10 percent, and the likelihood of taking an educational loan by 185 percent. This rise implies an increase in private educational expenditures of Rs. 195 billion annually[17], which is approximately 17 percent of India's total budgeted education expenditures[18] and about 0.7% of India's GDP[19]. In particular, the effects are more pronounced for poorer sections of the population.

The strong complementarity between education and health provides valuable insights into allocating government resources efficiently. Given that health coverage increases private household educational expenditures, policymakers may focus on measures that maximize the effectiveness of these increased educational investments. Even a reallocation of resources between health and education to achieve higher efficiency levels can also be considered. Moreover, as health coverage effects tend to be more pronounced for poorer populations, it is expected that this coverage would provide a faster educational catch-up between poor and non-poor populations, ultimately resulting in a reduction in educational disparities and, therefore, earnings inequality. As such, understanding and measuring these unintended benefits is essential for policymakers' efficient resource allocation.

[17]Population of India in 2023 is 142.86 crores (Source: Work Bank). The total annual increase in education spending = $1428627663 \times 12 \times 11.4$ = INR 195.44 billion

[18]Indian government's education budget in the Union Budget 23-24 was INR 1.12 trillion (Source: Economic Times; https://economictimes.indiatimes.com/?back=1(accessedon31stMarch,2023).

[19]Indian government's total expenditure on education as a percentage of GDP in 2020 was 4.3% (Source: World Bank). Increase in education budget as a percentage of GDP = $4.3 \times 17/100 = 0.73$.

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10 Appendix

10.1 Within difference improves efficiency over OLS

Let the regression equation be

$$y_{it} = \beta_{ols} X_{it} + \alpha_i + \epsilon_{it}$$

Let

$$v_{it} = \alpha_i + \epsilon_{it}$$

$$= \quad Var(v_{it}) = Var(\alpha_i + \epsilon_{it})$$

Assuming $\epsilon \quad \alpha$,

$$Var(v_{it}) = Var(\alpha_i) + Var(\epsilon_{it})$$

After within transformation,

$$(y_{it} - \bar{y_i}) = \beta_{wd}(X_{it} - \bar{X_i}) + (\epsilon_{it} - \bar{\epsilon_i})$$

where

$$\bar{y_i} = \sum^{t} y_{it}, \bar{X_i} = \sum^{t} X_{it}, \bar{\epsilon_i} = \sum^{t} \epsilon_{it}$$

$$\begin{aligned} = \quad Var(\epsilon_{it} - \bar{\epsilon_i}) &= Var(\epsilon_{it} - \bar{\epsilon_i}) \\ &= Var(\epsilon_{it}) - 0 \\ &< Var(v_{it}) \end{aligned}$$

$$= Var(\beta_{wd}) < Var(\beta_{ols})$$

10.2 Tables

Table 1: Comparison of Educational Investment Impacts of Aarogyasri Across Different Control Groups

	Coefficient			
	β_2^s	β_2^m	β_2^l	
Control Group	**Education Share**	**Education Expenditure**	**Education Loan**	**Observations**
Benchmark	0.0031	11.368	0.0368	47,194
	0.00134	3.86813	0.00388	
Benchmark + Outlier	0.0032	10.379	0.0371	51,148
	0.00131	3.70484	0.00375	
Large States in Benchmark	0.0017	15.74	0.0372	25,933
	0.00166	3.91845	0.00481	
Neighbour States in Benchmark	0.0044	18.919	0.0319	10,562
	0.00154	8.68032	0.00429	
Non-neighbour States in Benchmark	0.0029	10.637	0.0369	40,571
	0.00139	3.57496	0.00401	
Orissa	0.0009	14.003	0.033	7,948
	0.00187	11.70129	0.00493	
Other states with health insurance	0.0031	-0.895	0.0241	32,563
	0.00131	3.8882	0.00374	

Notes: Indicated interaction term coefficients for Equation 13-Equation 15 using data from IHDS 2004-05 and 2011-12. Each row presents a comparison between Andhra Pradesh and a distinct control group. Benchmark group includes Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa and Chhatisgarh. Outliers include Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Assam, Goa, and all union territories. Large states include Uttar Pradesh, Bihar, Madhya Pradesh, and Rajasthan. Neighbour states include Chhattisgarh and Orissa. Non-neighbour states include Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, and Jharkhand. Other states with health insurance include Tamil Nadu, Maharashtra, Gujarat, Kerala, Karnataka, and West Bengal. Standard errors reported in parentheses are robust. $p < 0.1$, $p < 0.05$, $p < 0.01$. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 2: Comparison of Educational Investment Impacts of Aarogyasri Across Different Household Types

	Coefficient			
	β_2^s	β_2^m	β_2^l	
Household Type	**Education Share**	**Education Expenditure**	**Education Loan**	**Observations**
Below Poverty Line Ration Card Holder	0.0058	18.126	0.0335	16,902
	0.00143	2.68111	0.00404	
Atleast One Member Attending School/College	0.0054	10.647	0.0475	29,176
	0.00185	4.9781	0.0059	
All School-Going Members Attending Private School	0.0041	19.576	0.0315	25,231
	0.00172	5.09160	0.00472	
Atleast One Member Below 18 Years Age	0.0067	12.663	0.0431	33,614
	0.00156	4.08319	0.00497	
Atleast One Member Below 24 Years Age	0.0045	8.418	0.0401	38,586
	0.00146	3.78378	0.00448	

Notes: Indicated interaction term coefficients for Equation 13-Equation 15 using data from IHDS 2004-05 and 2011-12. Each row corresponds to a comparison between distinct subsamples of households from Andhra Pradesh and other states, delineated by the specified characteristic. Standard errors reported in parentheses are robust. $p < 0.1$, $p < 0.05$, $p < 0.01$. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 3: Effect of Aarogyasri on Educational Investments with Additional Control Variables Included in the Benchmark Regression

	Coefficient of AP×Year2011			
	Education	**Education**	**Education**	
Control Variable Added to Eq (9-11)	**Share**	**Expenditure**	**Loan**	**Observations**
Household Life Expectancy	-0.0084	1.305	0.0279	47,194
	0.00314	9.10104	0.0082	
No. of HH Members Attending School/College	0.0082	15.276	0.037	47,194
	0.0013	3.87132	0.00388	
No. of HH Members Attending Private School	0.0043	12.239	0.0368	47,194
	0.0013	3.85494	0.00388	
No. of HH Members Less Than 24 Years Age	0.0034	11.545	0.0365	47,194
	0.00134	3.86151	0.00388	

Notes: Indicated interaction term coefficients for Equation 13-Equation 15 using data from IHDS 2004-05 and 2011-12. Each row displays coefficient estimates of the indicated interaction term subsequent to the inclusion of the specified control variable in the benchmark regression. Standard errors reported in parentheses are robust. $p < 0.1$, $p < 0.05$, $p < 0.01$. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 4: Disentangling the Effect of Aarogyasri and RSBY on Educational Investments

	Coefficients			
Variable	**Education Share**	**Education Expenditure**	**Education Loan**	
AP × Year2011	-0.0034	15.499	0.0228	
	0.00447	11.80655	0.01287	t̂68
RSBY × Year2011	0.0072	0.5523	-0.0053	
	0.00102	2.85067	0.00167	
RSBY × Year2011 × AP	0.0021	-5.1927	0.0213	
	0.00472	12.0971	0.01353	
Observations		47,023		

Notes: Indicated interaction term coefficients subsequent to adding the RSBY dummy and its interactions in Equation 13-Equation 15). Data from IHDS 2004-05 and 2011-12. Standard errors reported in parentheses are robust. $p < 0.1$, $p < 0.05$, $p < 0.01$. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 5: Districts Covered During Various Phases of Aarogyasri's Launch

Phase 1	Mahboobnagar	Srikakulam	Anantapur		
Phase 2	Rangareddy	Nalgonda	Chittoor	West Godavari	East Godavari
Phase 3	Medak	Karimnagar	Prakasam	Kadapa	Nellore
Phase 4	Adilabad	Kurnool	Hyderabad	Visakhapatnam	Vijayanagaram
Phase 5	Nizamabad	Warangal	Khammam	Guntur	Krishna

Source: YSR Aarogyasri Annual Reports

Table 6: Aarogyasri's Launch Dates Across Different Districts as Listed in Table 5

Policy Period	1	2	3	4	5
Phase 1	01.04.2007	05.04.2008	05.04.2009	05.04.2010	05.04.2011
Phase 2	05.12.2007	05.12.2008	05.12.2009	05.12.2010	05.12.2011
Phase 3		15.04.2008	15.04.2009	15.04.2010	15.04.2011
Phase 4		17.07.2008	17.07.2009	17.07.2010	17.07.2011
Phase 5		17.07.2008	17.07.2009	17.07.2010	17.07.2011

Source: YSR Aarogyasri Annual Reports

Table 7: Number of BPL families Covered Under Aarogyasri Across Various Phases (in lakhs)

Financial Year	2008-09	2009-10	2010-11	2011-12
Phase 1	25.27	27.66	27.47	26.67
Phase 2	48.23	52.02	49.49	49.49
Phase 3	38.45	39.52	39.52	38.44
Phase 4	36.44	36.44	35.46	38.19
Phase 5	39.80	44.91	42.86	45.46
Total	188.19	200.55	195.10	198.25

Source: YSR Aarogyasri Annual Reports

Table 8: Number of Treatments and Procedures Covered Under Aarogyasri Across Various Phases

Financial Year	2008-09	2009-10	2010-11	2011-12
Phase 1	272	942	938	938
Phase 2	330	352	938	938
Phase 3	272	942	938	938
Phase 4	330	330	352	192
Phase 5	330	330	352	192

Source: YSR Aarogyasri Annual Reports

Table 9: Number of Hospitals Empanelled Under Aarogyasri

Financial Year	2007-08	2008-09	2009-10	2010-11	2011-12
Government	13	95	97	97	98
Private	71	278	295	313	356
Total	84	373	392	410	454

Source: YSR Aarogyasri Annual Reports

Table 10: Proportion of Below Poverty Line (BPL) Ration Card Holding Households in the State

State	2004-05	2011-12
Andhra Pradesh	**0.87**	**0.90**
West Bengal	0.27	0.35
Gujarat	0.47	0.36
Maharashtra	0.33	0.27
Karnataka	0.77	0.68
Kerala	0.41	0.31
Tamil Nadu	0.51	0.46

Notes: Author's own computations using data from IHDS 2004-05 and 2011-12. Averages are weighted using the *hhweight* variable as constructed in the paper.

Table 11: Correlation Matrix for Predicted Errors in Equations (13-15)

		Eq(13)	**Eq(14)**	**Eq(15)**
		e^s	e^m	e^l
Eq(13)	e^s	1		
Eq(14)	e^m	0.69	1.00	
Eq(15)	e^l	0.16	0.13	1

Notes: The errors have been predicted after running OLS regressions on Equation 13-Equation 15 using data from IHDS 2004-05 and 2011-12. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 12: Percentage of population from other Indian states migrating with their household to Andhra Pradesh (in %)

	Pre 2001	2001-2006	2006-2011
	(A)	(B)	(C)
Control states[a]	0.006	0.003	0.003
Confounder states[b]	0.027	0.009	0.011
Confounder states, excluding south Indian states[c]	0.016	0.007	0.009
Confounder states, excluding states bordering Andhra Pradesh[d]	0.004	0.002	0.003

Notes: Author's own computations using data from 1991, 2001, and 2011 Census of India. [a]Without health insurance, [b]With health insurance, [c]Excluding Kerala, Karnataka and Tamil Nadu, [d]Excluding Kerala, Karnataka, Tamil Nadu, Maharashtra, and Chhattisgarh

Table 13: Variable Definitions

Variable	Definition
Outcome variables:	
Share of Education	Share of education in monthly consumption expenditure per household member on school/college tuition fees, coaching fees and educational articles
Education Expenditure	Monthly educational expenditure per household member on school/college tuition fees, coaching fees and educational articles, deflated by Tendulkar's poverty line (in INR)
Education Loan	Dummy variable equals 1 if a loan is taken by the household for educational purposes in the past 5 years, 0 otherwise
Control variables:	
Andhra Pradesh	Dummy variable equals 1 if the household resides in Andhra Pradesh, otherwise 0
Year	Dummy variable equals 1 if the year is 2011, otherwise 0
Consumption Expenditure	Monthly consumption expenditure per household member, deflated by Tendulkar's poverty line (in INR)
Urban Location	Dummy variable equals 1 if the household resides in an urban location, 0 otherwise
Household Size	Total number of members in a household

Poor Household	Dummy variable equals 1 if the monthly consumption expenditure per household member is below Tendulkar's poverty line, 0 otherwise
Female Household Head	Dummy variable equals 1 if the household head is female, 0 otherwise
Household Head Education	Number of years of schooling of household head
Brahmin Caste	Dummy variable equals 1 if the household belongs to brahmin caste, 0 otherwise
Household Employment Stability	Number of household members employed in permanent job, own business or own farm
Treatment for Long Term Illness	Number of household members receiving medical treatment for long term illness in the past 12 months
Own house	Dummy variable equals 1 if the household owns a house, 0 otherwise
Own durable goods	Dummy variable equals 1 if the household owns less than 5 durables amongst cycle/bicycle, sewing machine, generator set, mixer/grinder, motor cycle/scooter, television, cooler, clock/watch, electric fan, table/chair, cot, telephone, mobile phone, fridge/refrigerator, pressure cooker, cable/dishTV, car, A.C., washing machine, computer, laptop, credit card, microwave oven, and 0 otherwise.
Own land	Dummy variable equals 1 if the household owns agricultural land, 0 otherwise

Table 14: Potential Confounders

Confounder	**Identification Strategy**	**Bias in $\hat{\beta}_2$ estimate**
Selectivity in BPL ration card holding	Considering the entire population of Andhra Pradesh, BPL as well as APL, as the treatment group	Subdued
State sponsored health insurance schemes introduced in other Indian states between 2004-05 to 2011-12 [a]	Excluding such states from the control group	Subdued
Debt financing of education	Including the likelihood of taking an education loan as a dependent variable and estimating the system of equations using SUREG	Subdued
Direct Benefit Transfer (DBT) educational scholarships	Controlled for as a part of household consumption expenditure	Subdued
Central government health insurance programmes introduced between 2004-05 to 2011-12 [b]	Examine if the effect of RSBY on educational investments varies between Andhra Pradesh and the control states	No
Jawahar Bal Aarogya Raksha Yojana (2010)	Examine the impact of Aarogyasri on households ineligible for JBARY	Negative
Microfinance crisis (2010)	Compare Andhra Pradesh with a subset of control states highly impacted by the crisis	Inconclusive

Rising number of school or college going children in Andhra Pradesh	Controlling for the number of school and college going household members in regression	Negative

[a]Chief Minister's Comprehensive Insurance Scheme (2007, TN), Mahatma Jyotiba Phule Jan Arogya Yojana (2012, Maharashtra), Mukhyamantri Amrutum Yojana (2012, Gujrat), Karunya Health Scheme (2012, Kerala), Vajpayee Arogyasri Yojana (2010, Karnataka), West bengal health scheme (2008, WB), Kalaignar Kapitu Thittam (2009, TN)

[b]Rashtriya Swasthya Bima Yojana (2007), Aam Aadmi Beema Yojana (2007)

Table 15: Higher increase in educational investments for Andhra Pradesh between 2004-05 and 2011-12 as compared to the control states

		Andhra Pradesh			Control States[a]			
		2004-05	2011-12	Diff	2004-05	2011-12	Diff	Diff
		(A)	(B)	(B - A)	(C)	(D)	(D - C)	(B - A) - (D - C)
Share of education in total expenditure[b]	Rural	0.03	0.04	0.01	0.03	0.04	0.01	0.002
	Urban	0.05	0.07	0.02	0.06	0.07	0.02	0.004
	Total	0.03	0.05	**0.02**	0.03	0.05	**0.01**	**0.002**
Real education expenditure[c]	Rural	20.6	62.2	41.6	20.7	39.8	19.1	22.5
	Urban	63.2	115.4	52.2	62.4	111.4	49.1	3.1
	Total	29.6	74.3	**44.7**	27.3	52.4	**25.1**	**19.6**
Proportion of loan takers[d]	Rural	0.01	0.05	0.04	0.00	0.01	0.01	0.04
	Urban	0.05	0.11	0.06	0.01	0.03	0.02	0.05
	Total	0.02	0.06	**0.05**	0.01	0.01	**0.01**	**0.04**

Notes: Author's own computations using data from IHDS 2004-05 & 2011-12; [a]Includes Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa and Chhatisgarh. [b] Share of education in monthly per capita total consumption expenditure of the household. [c] Real monthly per capita education expenditure of the household. [d] Proportion of households that took an education loan in the past five years. Averages are weighted using the *hhweight* variable as constructed in the paper.

Table 16: Higher increase in educational investments for BPL households in Andhra Pradesh between 2004-05 and 2011-12 as compared to the BPL households in control states

		Andhra Pradesh				Control States[a]					
		2004-05		2011-12		2004-05		2011-12		Diff	
		APL[e]	BPL[f]	APL	BPL	APL	BPL	APL	BPL	APL	BP
		(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(C-A)-(G-E)	(D-B)-(
Share of education	Rural	0.07	0.02	0.02	0.04	0.04	0.02	0.05	0.04	-0.06	0.0
in total expenditure[b]	Urban	0.06	0.04	0.04	0.07	0.06	0.04	0.07	0.05	-0.03	0.0
	Total	0.07	0.03	0.03	0.04	0.04	0.03	0.05	0.04	**-0.05**	**0.0**
Real education	Rural	38.4	16.2	23.5	29.8	22.2	10.9	32.7	21.4	-25.4	3.
expenditure[c]	Urban	61.8	27.5	38.1	67.9	45.9	23.3	61.6	35.5	-39.4	28.
	Total	47.1	17.7	29.3	36.5	26.2	11.9	37.5	22.9	**-29.1**	**7.**
Proportion of	Rural	0.00	0.00	0.10	0.04	0.00	0.00	0.01	0.01	0.09	0.0
education loan	Urban	0.01	0.04	0.05	0.08	0.01	0.00	0.02	0.02	0.03	0.0
takers[d]	Total	0.00	0.01	0.08	0.04	0.01	0.00	0.01	0.01	**0.08**	**0.0**

Notes: Author's own computations using data from IHDS 2004-05 & 2011-12. [a] Includes Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa and Chhatisgarh. [b] Share of education in monthly per capita total consumption expenditure of the household. [c] Real monthly per capita education expenditure of the household. [d] Proportion of households that took an education loan in the past five years. [e] Above poverty line. [f] Below poverty line. The sample of BPL households has been restricted to households below 80 percent quantile of real monthly per capita consumption expenditure. Averages are weighted using the *hhweight* variable as constructed in the paper.

Table 17: Assessing covariate balance between Andhra Pradesh and control states using mean differences

	Andhra Pradesh		Control States					
	2004-05	2011-12	2004-05	2011-12	Diff	P-value	Diff	P-value
Variable [b]	(A)	(B)	(C)	(D)	(A-C)	(E)	(B-A)-(D-C)	(F)
Household Characteristics								
Per capita consumption expenditure	831.8	1314.4	658.4	943.8	173.4	<0.001	197.2	<0.001
Poor	0.07	0.05	0.32	0.23	-0.24	<0.001	0.07	<0.001
Rural	0.21	0.23	0.16	0.18	0.05	0.8	0.00	<0.001
Household size	5.80	4.32	8.12	5.70	-2.32	<0.001	0.94	<0.001
Female household head	0.06	0.12	0.05	0.13	0.01	0.1	-0.01	0.25
Education of household head	5.82	6.90	7.13	7.34	-1.31	<0.001	0.87	<0.001
Brahmin caste	0.01	0.01	0.07	0.06	-0.06	0.0	0.01	<0.001
Regular employment	0.14	0.26	0.23	0.37	-0.09	<0.001	-0.02	<0.001
Household Members' Health								
Treatment for long term illness	0.32	0.38	0.24	0.52	0.08	<0.001	-0.22	<0.001
Long term illness	0.24	0.30	0.15	0.31	0.09	<0.001	-0.10	<0.001
Workdays lost in 30 days	0.56	1.52	0.49	1.02	0.06	<0.001	0.43	0.016
Workdays lost in 12 months	8.28	4.52	2.19	4.97	6.09	<0.001	-6.55	<0.001
Household Health Finance								
Access to pvt/public health insurance	0.02	0.10	0.02	0.13	-0.01	0.0	-0.02	0.108
Share of medical expenditure	0.14	0.14	0.09	0.11	0.05	<0.001	-0.02	<0.001
Share of inpatient medical expenditure	0.06	0.07	0.03	0.05	0.03	0.5	0.00	<0.001
Household Ownership of Goods								
Own house	0.92	0.90	0.97	0.97	-0.05	<0.001	-0.02	<0.001
Own durable goods	0.30	0.15	0.49	0.34	-0.19	0.6	0.01	<0.001
Own land	0.40	0.97	0.61	0.96	-0.22	<0.001	0.23	<0.001
Observations	1975	1975	21682	21682				

Notes: Author's own computations using data from IHDS 2004-05 & 2011-12. [a] Includes Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa, and Chhatisgarh. [b] Refer to Table 13 for variable descriptions. Averages are weighted using the *hhweight* variable as constructed in the paper.

Table 18: Higher increase in the proportion of BPL households for Andhra Pradesh between 2004-05 and 2011-12 compared to control states

	Andhra Pradesh			Control States[a]			Control+Outlier[b]		
	2004-05	2011-12	Diff	2004-05	2011-12	Diff	2004-05	2011-12	Diff
	(A)	(B)	(B-A)	(C)	(D)	(D-C)	(E)	(F)	(F-E)
Rural	0.92	0.94	0.03	0.39	0.39	0.00	0.39	0.39	-0.0001
Urban	0.67	0.78	0.12	0.20	0.24	0.04	0.20	0.24	0.04
Total	0.87	0.90	**0.03**	0.36	0.36	**0.003**	0.36	0.36	**0.002**

Notes: Author's own computations using IHDS 2004-05 & 2011-12. [a]A subset of other Indian states including Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa, and Chhatisgarh; [b]Includes outliers (Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Assam, Goa, and all union territories) in the benchmark control group. Averages are weighted using *hhweight*

Table 19: Testing for parallel trends in 2004-05

Sample	**Variable**	**Coefficient of AP × Year2011**
All households in Andhra Pradesh and the control states[a]	Share of education in total expenditure	2.00E-10*
	Real education expenditure	7E-08
	Probability of education loan	4E-13
BPL[b] households in Andhra Pradesh and the control states	Share of education in total expenditure	2.00E-10*
	Real education expenditure	2E-16
	Probability of education loan	-2E-11

Notes: Indicated interaction term coefficients for Equation 8 using data from IHDS 2004-05 and 2011-12. [a] Includes Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa, and Chhatisgarh. [b] Below poverty line. $p < 0.1$. Regressions are weighted using the *hhweight* variable as constructed in the paper.

Table 20: Placebo Test Results

	Education Share		**Education Expenditure**		**Education Loan**		**Positive and Significant**^{a}
Placebo State	**Coeff**	**P-val**	**Coeff**	**P-val**	**Coeff**	**P-val**	
Jammu & Kashmir	0.01	0.035	22.1	0.054	0.001	0.818	No
Himachal Pradesh	-0.02	0.166	-11.1	0.661	0.006	0.729	No
Punjab	-0.01	0.055	16.1	0.029	-0.005	0.235	No
Uttaranchal	-0.015	0.000	-3.2	0.768	0.003	0.463	No
Haryana	-0.004	0.303	21.5	0.010	-0.0001	0.984	No
Delhi	0.017	0.020	61.7	0.001	0.006	0.492	No
Rajasthan	-0.002	0.120	-2.7	0.278	0.00	0.186	No
Uttar Pradesh	0.005	0.000	-3.0	0.163	-0.005	$<$0.001	No
Bihar	0.003	0.003	0.8	0.758	0.001	0.524	No
Jharkhand	-0.004	0.003	-3.7	0.119	-0.001	0.676	No
Orissa	0.001	0.351	-2.7	0.664	0.00	0.770	No
Chhatishgarh	-0.006	0.0001	-11.7	$<$0.001	0.006	0.049	No
Madhya Pradesh	-0.0011	0.3541	-5.9905	0.0046	0.004	0.1473	No

Notes: [a]The coefficients for all three variables are positive and significant at 5% level. [b] Control group for each placebo state includes all 12 states in the group Jammu and Kashmir, Himachal Pradesh, Punjab, Uttaranchal, Haryana, Delhi, Rajasthan, Uttar Pradesh, Bihar, Jharkhand, Orissa, and Chhatisgarh, except for the placebo state.

10.3 Graphs

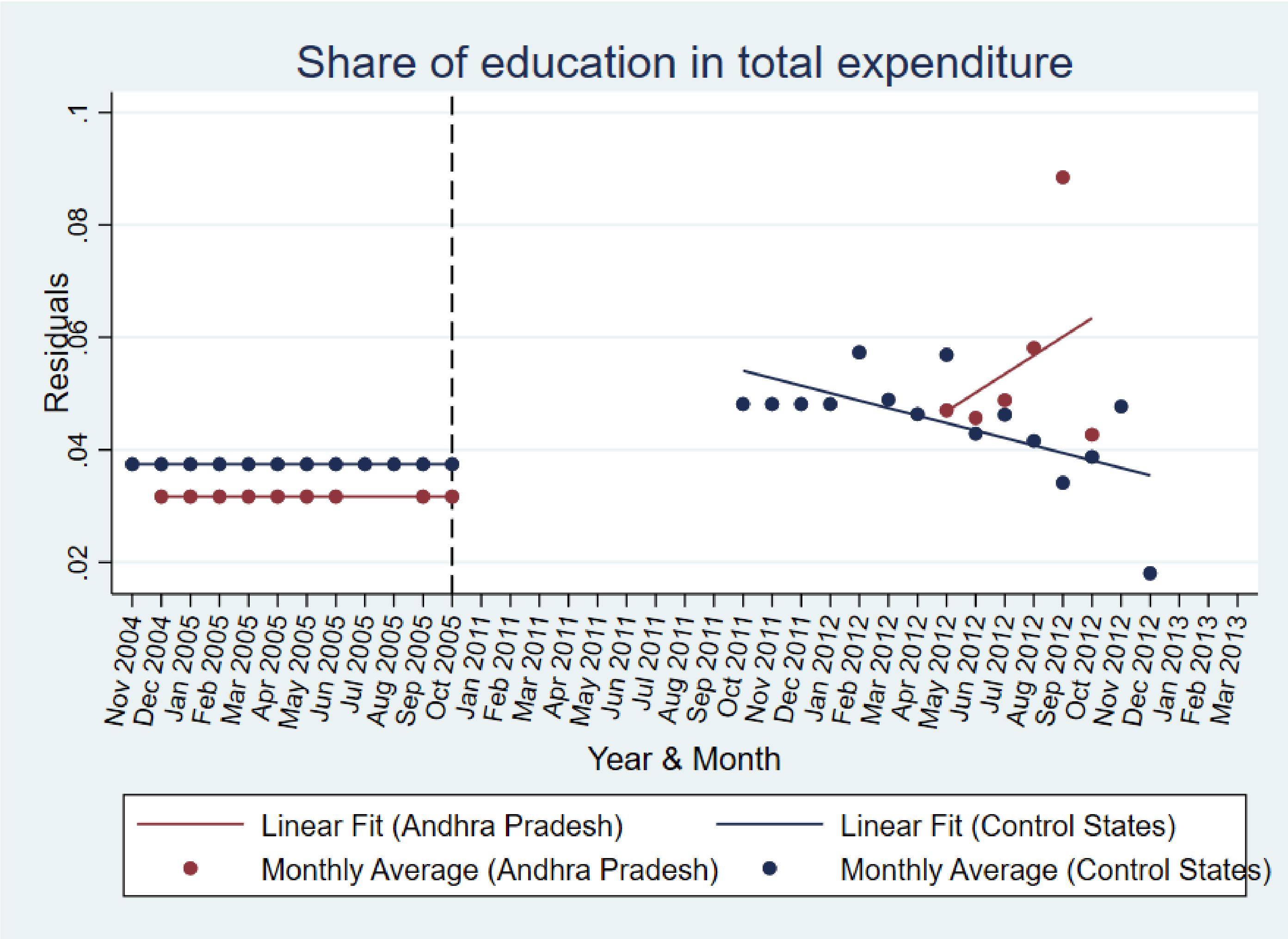

Figure 2: Linear fit on monthly averages for the share of education in monthly per capita consumption expenditure of the households in Andhra Pradesh and the control states

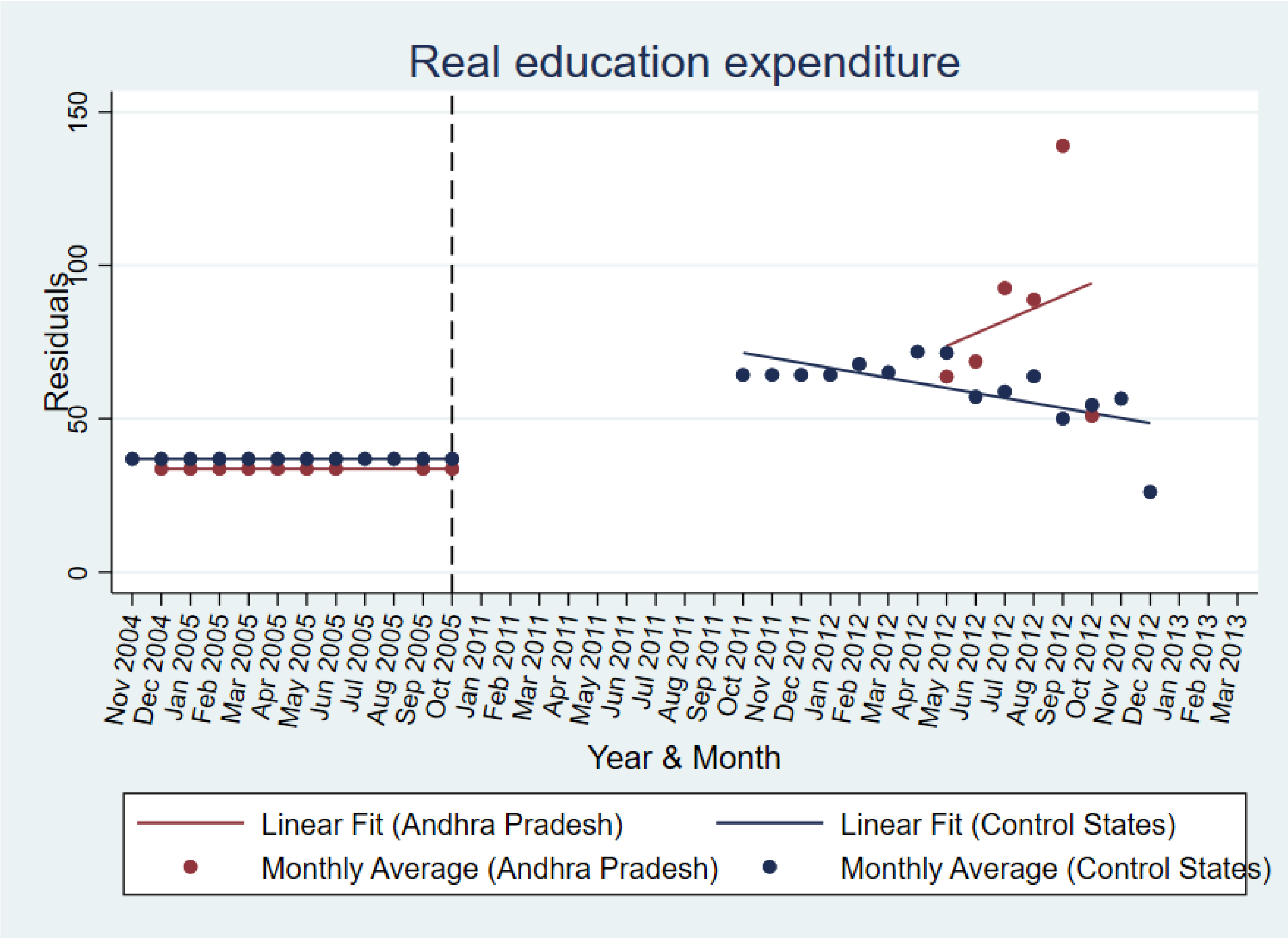

Figure 3: Linear fit on monthly averages for real monthly per capita education expenditure of the households in Andhra Pradesh and the control states

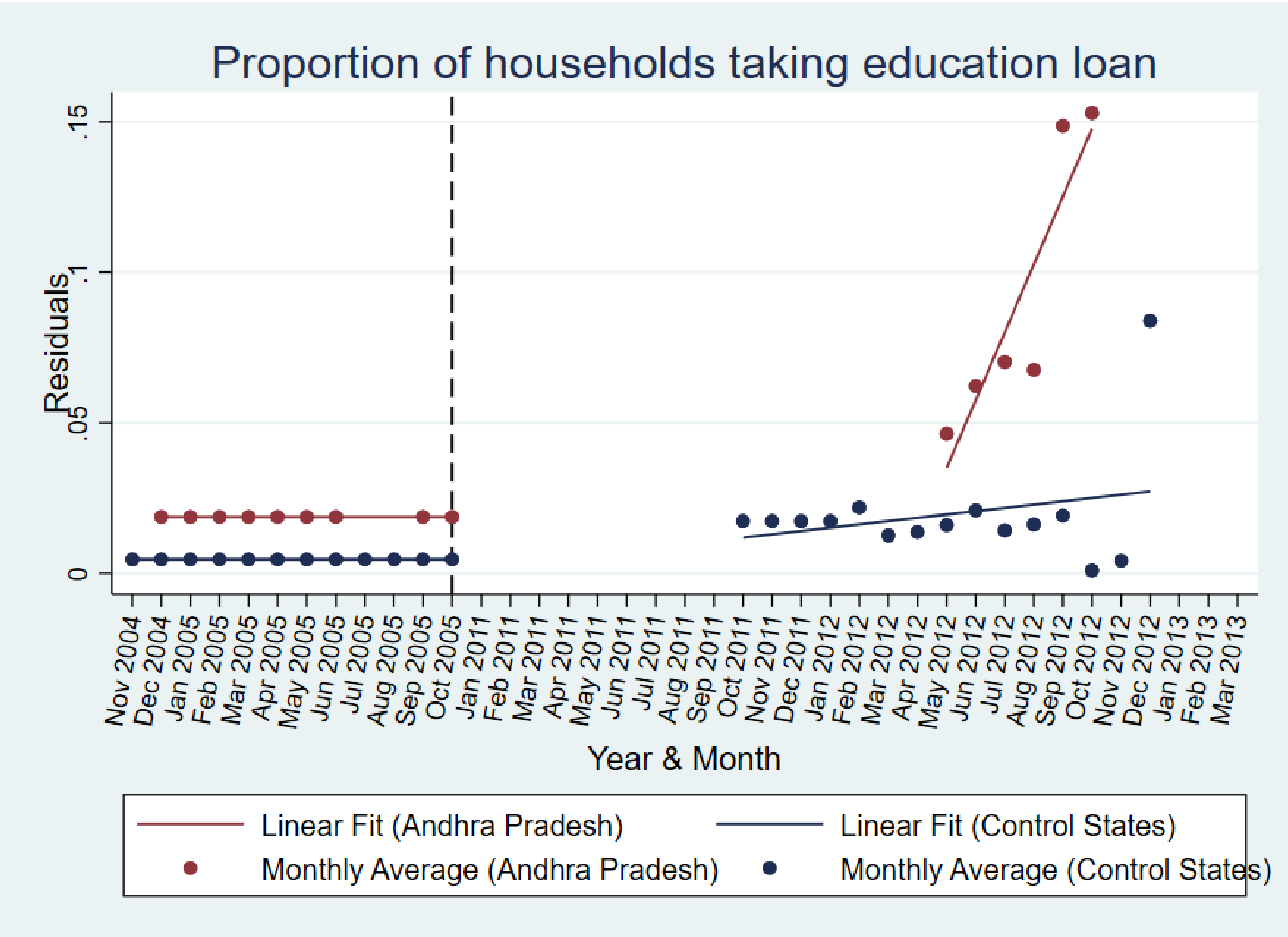

Figure 4: Linear fit on monthly averages for the proportion of households taking education loan in Andhra Pradesh and the control states

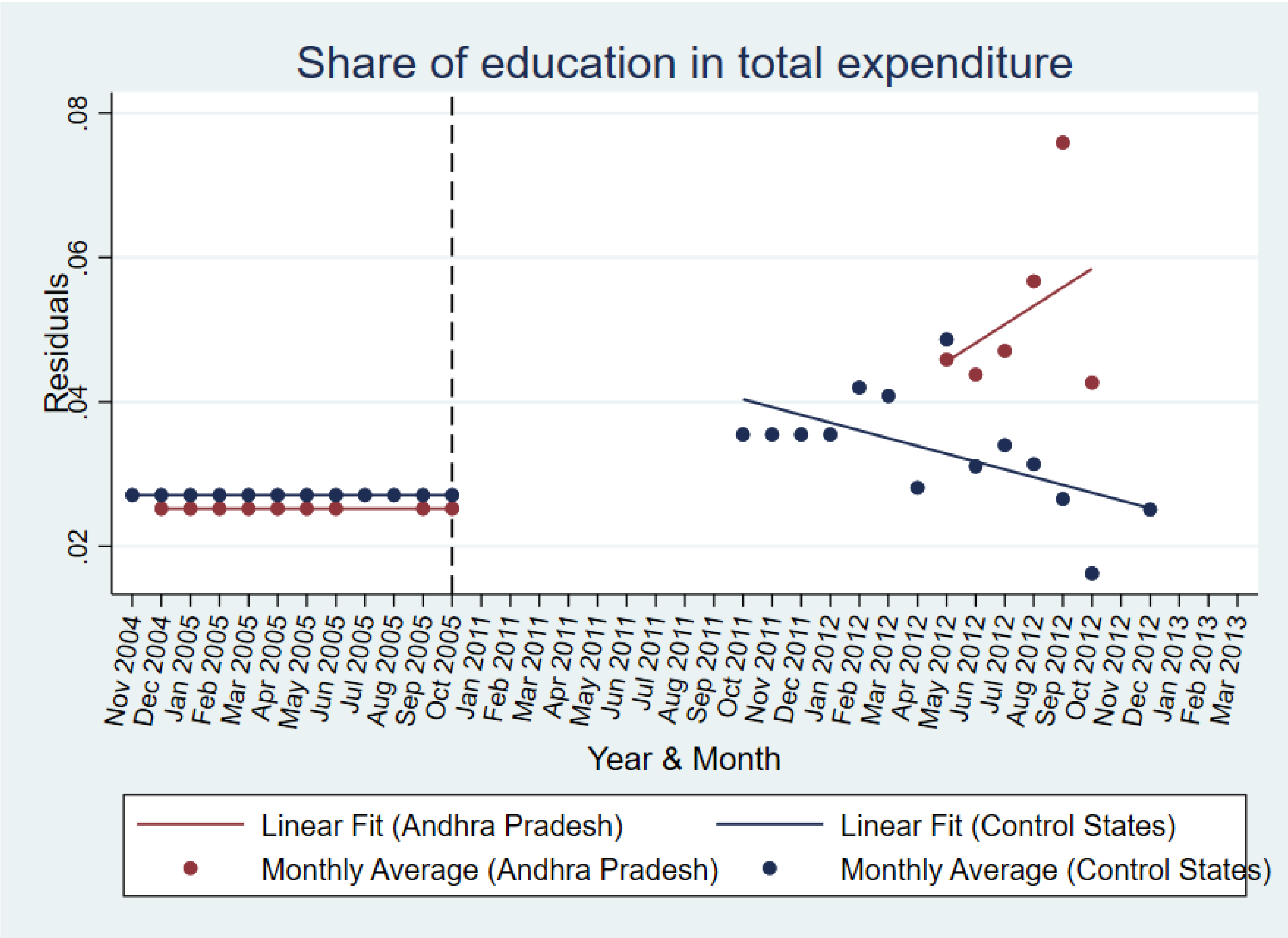

Figure 5: Linear fit on monthly averages for the share of education in monthly per capita consumption expenditure of BPL households in Andhra Pradesh and the control states

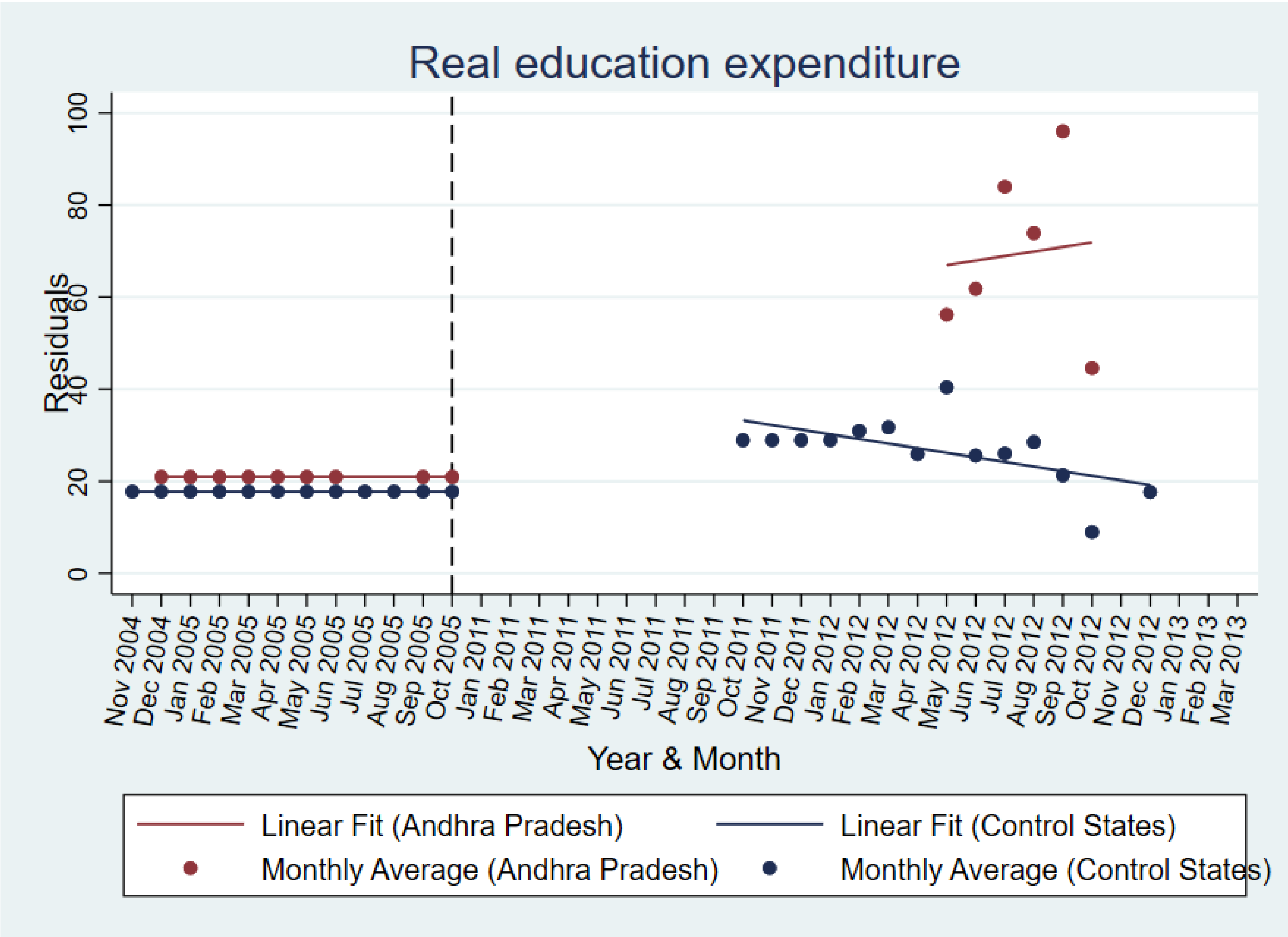

Figure 6: Linear fit on monthly averages for real monthly per capita education expenditure of BPL households in Andhra Pradesh and the control states

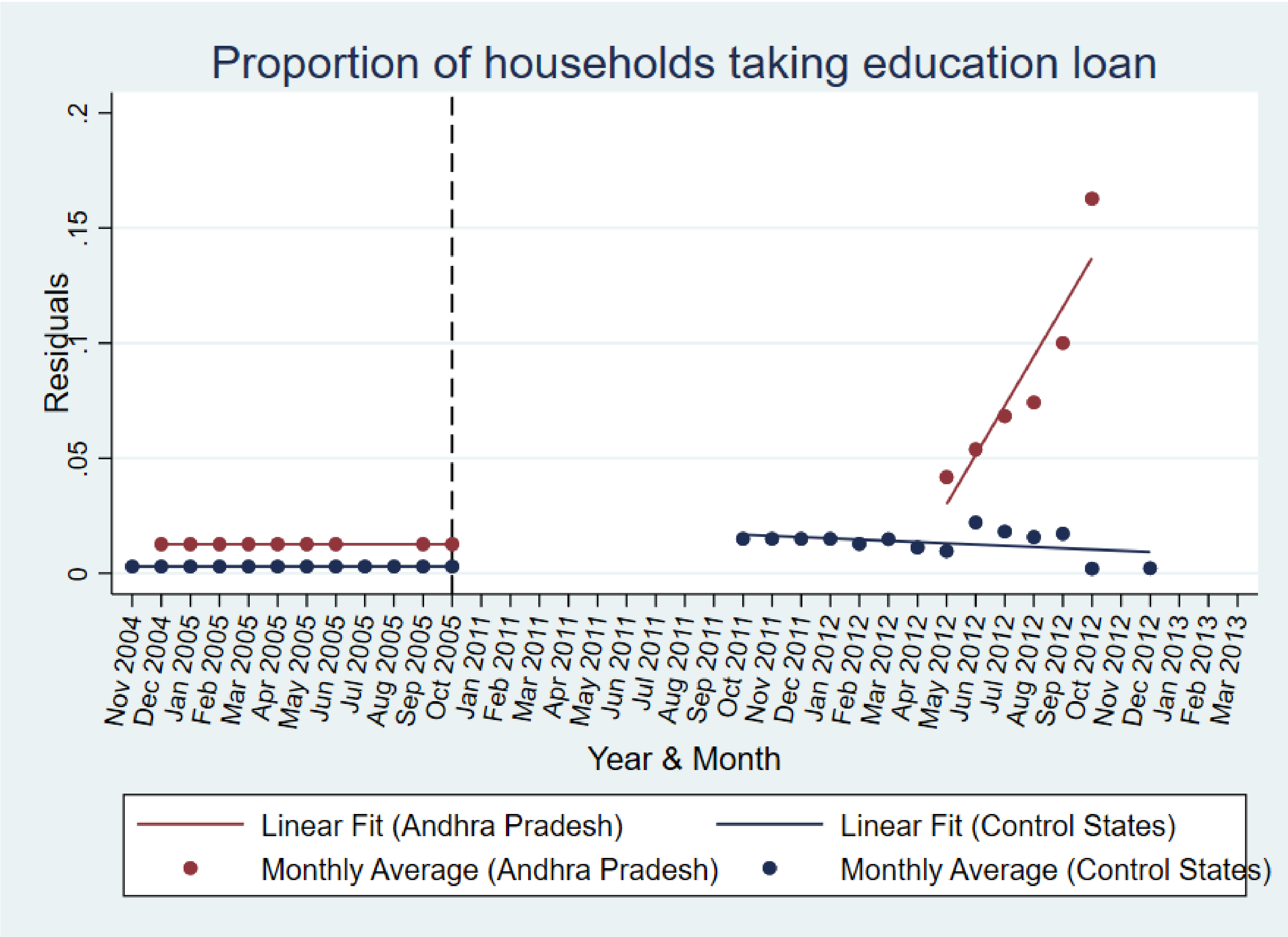

Figure 7: Linear fit on monthly averages for the proportion of BPL households taking education loan in Andhra Pradesh and the control states

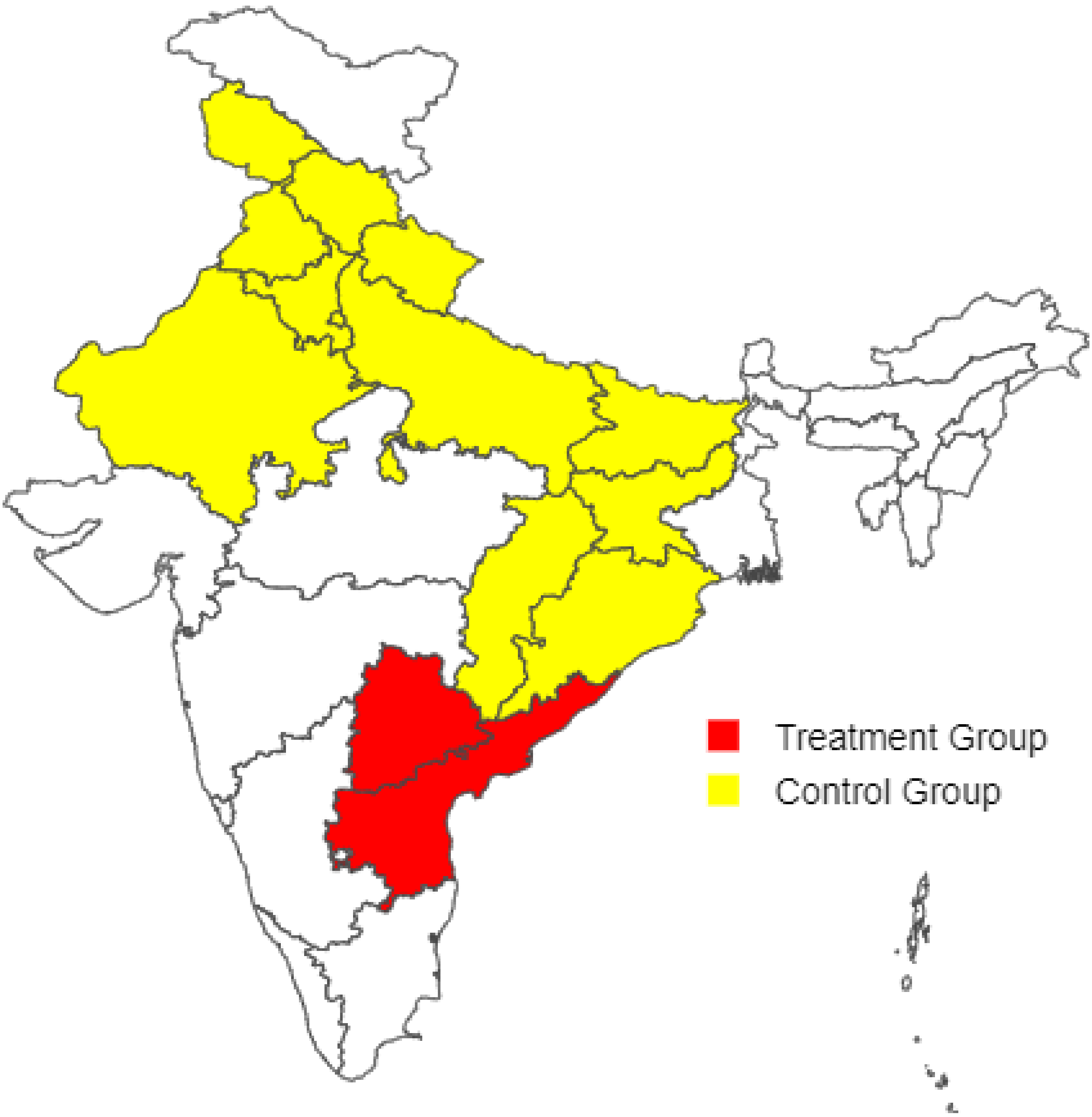

Figure 8: Map of India: Treatment and control group

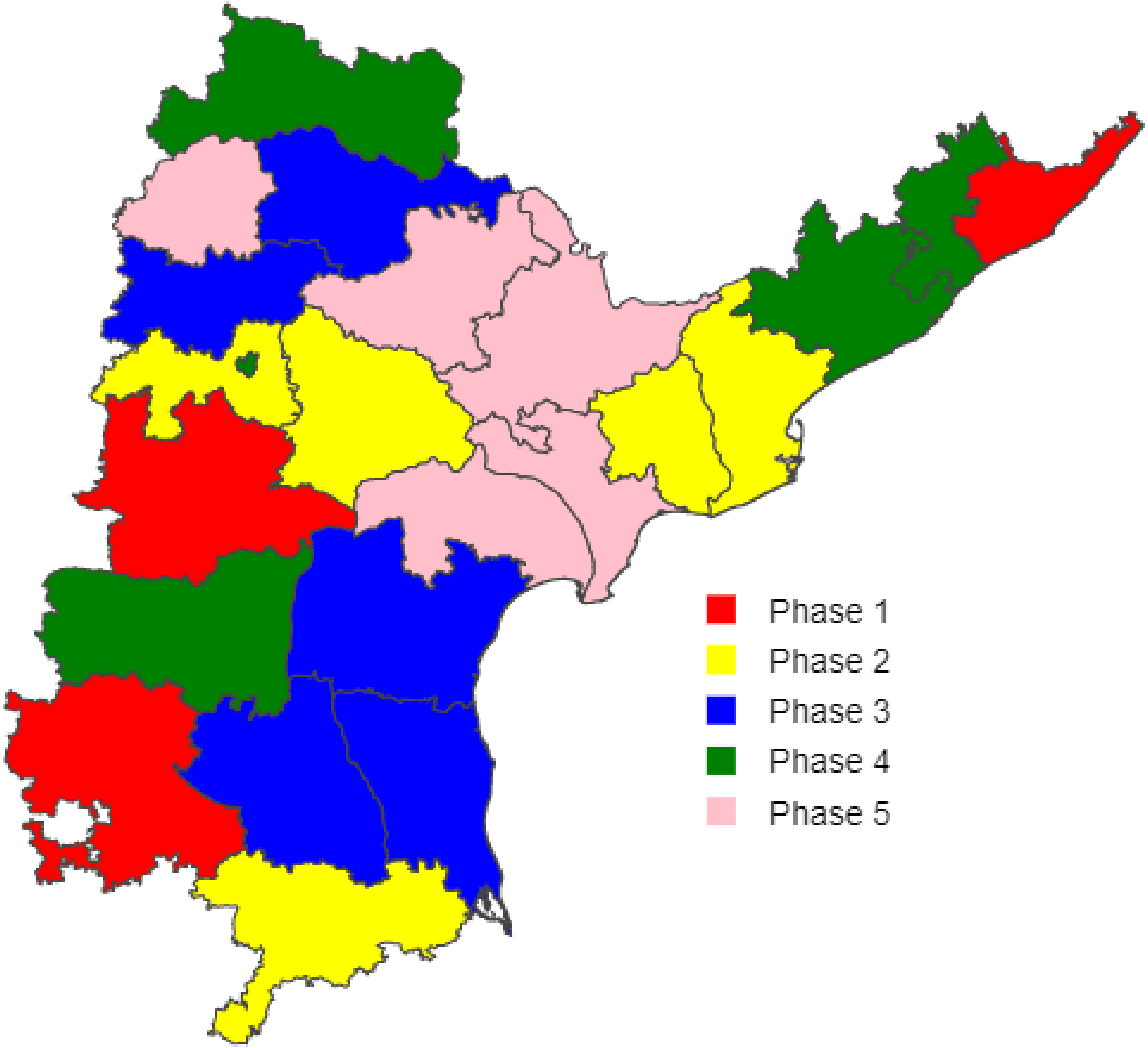

Figure 9: Map of Andhra Pradesh (pre partition in 2014): Phases for Arogyasri scheme implementation