Essays in Environmental and Health Economics

by

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Abstract

This dissertation contains three distinct chapters considering different challenges faced by a developing country; India.

Chapter 1. Food price spikes induced by hot weather could be a threat to food security, human health and poverty. It could exacerbate the health status of households by reducing the nutrient food choices, particularly among the vulnerable groups who already have a more frail status. This paper examines the first possible causal link between milk average market price and hot weather in the short run at the household level in India. Using Human Development Survey data, it is empirically showed that hot weather has a significant adverse impact on the price in rural India. The impacts are more pronounced for non-poor families in both rural and urban areas. The effects are robust to alternative heat metrics. The paper further investigates the effect of hot weather on households' milk consumption. Evidence suggests that low-income (poor) families with purchased consumption, both in rural and urban areas, are significantly adversely affected compared to those with homegrown product.

Chapter 2. Health-related behaviour and, in particular, attending antenatal care during pregnancy is essential to reduce the risk of pregnancy complications, stillbirth, and maternal mortality. This paper estimates the causal effect of years of formal education on the likelihood that a pregnant woman in India attends natal care and screening services. Despite the importance, insufficient documents exist on the determinants of natal care usage in developing countries. The current study investigates for the first time the hypothesis that women's schooling attainments might have a causal impact on natal care usage in India. Drawing on the nationally representative India Human Development Survey (IHDS-II) and instrumenting for years of schooling with plausibly exogenous variation in age at first menarche, I find that delayed age at menarche significantly increases formal education. Further, evidence suggests that an additional year of schooling significantly enhances the likelihood of uptaking the antenatal checkups. However, attending a sonogram/ultrasound does not appear to be significant.

Chapter 3. Adolescent girls are amongst the vulnerable groups exposed to the risks that challenge their healthy development into young women. India's Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (SABLA) program was designed to address such challenges by building health awareness and encouraging decision-making autonomy as the first steps towards real change in women's development. Using data from the nationally representative India Demographic and Health Survey (IDHS), with plausibly exogenous variation in the program's rollout across districts and birth cohorts, we provide evidence that exposure to SABLA increases the likelihood of having knowledge of family planning and diarrhoea treatment, using contraception, and autonomy in personal financial decision-making for exposed women. The effects are more pronounced for women residing in urban areas, for women who have secondary education or higher, and primarily for Muslim women.

Declaration of Authorship

I, Modjgan Alishahi, declare that this thesis titled, "Essays in Environmental and Health Economics" and the work presented in it are my own. Chapter three of this thesis was done jointly with Dr. Samira Hasanzadeh, My contribution is equal to hers.

I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ________________________________

Date: 2022 July 9

General Introduction

This dissertation employs a diverse set of economic tools to investigate three different questions in environmental and health economics. The essays presented in these three chapters also intend to contribute to development economics.

Food price spikes induced by hot weather could be a threat to food security, human health and poverty. It could exacerbate the health status of households by reducing the nutrient food choices, particularly among the vulnerable groups who already have a more frail status.

In the first chapter, I investigate the first possible causal link from hot weather to the price of milk in India in the short-term (a horizon of 30-days). I use data from the India Human Development Survey (IHDS), asking detailed questions about household members and their socioeconomic status. India offers an engaging context within which we can study the impact of hot weather in general, and its price impact in particular mainly due to its exposure to unusual and unprecedented spells of hot weather, its agricultural-oriented economy with being vulnerable to such large weather shocks and being the world's largest milk producer with low milk consumption and high level of malnutrition. The study design allows for a clean identification as hot weather is exogenously determined. That, is controlling for place and time the realization of heat metric is good as random.

The results suggest that (a) a 1°C increase in average daily maximum temperature across the 30-day time frame causes a 0.66% increase in milk market price per litre in rural areas; (b) given other things equal, the effect is more pronounced in non-poor households in both rural and urban India. I further investigate the effect of hot temperature on milk consumption concerning home-produced and purchased in the market consumption in rural and urban areas. Evidence suggests that temperature shocks disproportionately impact consumption depending on the household status. This paper builds on the literature on the economic effect of climate change in India by being the first to consider the local price impacts of hot weather faced by the households in the short-term. We owe this to a feature of our setting that provides us with detailed and disaggregated information that allows us to attain the local prices each household faces coupled with their living circumstances, as well as the local conditions that could drive the milk market price.

Second chapter examines the potential advantages of schooling regarding health-related behaviour among pregnant women. Maternal healthcare and, in particular, antenatal care is acknowledged to be central to a woman's well-being. It contributes to both mothers and their children's health by detecting and treating diseases and pregnancy-related complications, leading to reduced maternal morbidity and mortality. Insights from Grossman's human capital model suggest that educational attainment as an input among several others in the health production function can lead to better health and health behaviours. Women's elevated educational attainment can change their preferences and attitudes towards matters that impact their own and their offspring's health and well-being. Despite the need for education, 131 million primary school-aged girls are out of school, leading them to miss the opportunity to learn essential skills and build knowledge. However, identifying the effects of education on our outcomes may be a challenge, as educational choices are often endogenous.

I take the possible endogeneity problem of education to health behaviours into account and implement an Instrumental Variable (IV) strategy to overcome such issue. I investigate, for the first time, the hypothesis that women's schooling attainments have a causal effect on the likelihood that a pregnant woman in India attends natal care and screening services by instrumenting years of schooling with plausibly exogenous variation in age at first menarche. Using the first menarcheal age appears to be relevant in India's context as many girls, owing to cultural and societal barriers, drop out of school once they reach the menstruation age.

Drawing on the India Human Development Survey (IHDS) and using menarche age as an instrument for schooling, I find a significantly positive effect of years of schooling completed on the probability of undertaking the screening tests, however, I find no evidence that more years of schooling completed significantly raises the likelihood that women attend the ultrasound test. This paper contributes to the existing literature on the association between human capital (measured by women's schooling) and health behaviour by highlighting that it is not only literacy itself that matters; years of formal schooling also matter. It examines the effect of years of formal schooling on attending a wide range of screening tests from simple blood pressure tests to ultrasound examinations by instrumenting the schooling attainments by menarche age.

In the third chapter, we intend to test the effectiveness of a women empowerment policy - India's Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (SABLA). Adolescent girls are amongst the vulnerable groups exposed to the risks that challenge their healthy development into young women. The SABLA program was designed to address such challenges by building health awareness and encouraging decision-making autonomy as the first steps towards real change in women's development. We exploit plausibly exogenous variation in the program's rollout across districts and birth cohorts.

Using the DHS data coupled with the difference-in-differences approach, we find evidence suggestive of an improvement in some outcome measures. More precisely, exposure to SABLA leads to an increase in the likelihood of family planning awareness, use of contraception, personal financial decision-making, and diarrhea treatment knowledge. However, evidence suggests a more significant effect size for women with higher educational attainment and those who reside in urban settings. The Hindu respondents also were less advantaged in this regard. Our results are robust to alternative specifications. The placebo tests and randomization exercise combined with a visual inspection of the balance on observables provide us with some evidence against the potential endogenous assignment of the program to districts. Our findings call into question whether such intervention is an appropriate policy tool. Such policy given to the entire population seems ineffective in improving women's empowerment, at least for the components probed in this study. It might require the policy to focus directly on disadvantaged households in terms of education and place of residence.

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To Homayoun,
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Chapter 1

Hot Weather and Price of Milk: Evidence from the Experiences of 42,000 Indian Households

By Modjgan Alishahi

Abstract

Food price spikes induced by hot weather could be a threat to food security[1] and human health. It could exacerbate the health status of households by reducing the nutrient food choices particularly among the vulnerable groups who already have more frail status. This paper attempts to examine the first possible causal link between milk average market price and hot weather in the short run at household level. Using Human Development Survey data from India, we empirically show that hot weather has an adverse significant impact on the price in rural India. The impacts are more pronounced for middle and low-income (non-poor) families in rural areas compared to the urban non-poor households. The effects are robust to alternative heat metrics.

[1] "situation that exists when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their dietary needs and food preferences for an active and healthy life", The State of Food Insecurity in the World 2001 Food and Agriculture Organization, Rome

1.1 Introduction

Food price spikes associated with the warming world would be a potential threat to food security and human health globally (Bandara and Cai, 2014). The price surge has been identified to have a plausible negative impact on food intake, particularly those rich in nutrient (Cornelsen et al., 2015), and on the overall poverty in low-income countries (Ivanic and Martin, 2008). Milk, as one of the primary agricultural products with a predominant source of protein, is required for human growth and health. Thus, its local price fluctuations in response to hot weather resulting from weather-related insufficient supply can stress families, mainly those with young children, and deprived and susceptible groups when coping with the higher prices and the direct impact of local weather. These factors could adversely influence their financial and health status and consequently lead them to bear more health and well-being insecurity (Carty, 2012).

The current paper aims to investigate the first possible causal link from hot weather to the price of milk in India in the short-term (a horizon of 30-days). We use data from the India Human Development Survey (IHDS), a nationally representative survey of 42,152 households dwelling in 971 urban and 1,503 rural areas across India. The survey is a collaboration between the University of Maryland and the National Council of Applied Economic Research (NCAER) in New Delhi. It asks detailed questions about household members and their socioeconomic status.

India offers an engaging context within which we can study the impact of hot weather in general, and its price impact in particular. Firstly, the region is subject to unusual and unprecedented spells of hot weather.[2] Secondly, as a developing country with an agricultural-oriented economy, it is particularly susceptible to such large weather shocks owing to its poorly developed infrastructure, high population density, the proximity of settlement to farms and production centers, storage (cooling facilities, refrigerator), distribution, and logistics (Cervantes-Godoy and Dewbre, 2010; Fisher et al., 2012; Schlenker and Roberts, 2009). Finally, despite being the world's largest milk producer,[3] and providing roughly 21% of global production,[4] its consumption remains low and malnutrition remains high (Muehlhoff et al., 2013).

The question that we focus on as our dependent variable asks respondents to report on

[2] http://www.dw.com/en/india-climate-change-ipcc/a-58822174
[3] http://www.fao.org/india/fao-in-india/india-at-a-glance/en/
[4] http://www.fao.org/ag/humannutrition/nutritioneducation/49741/en/

average market price over the past 30 days before the interview date. We map the answer to that question to what we know about temperature in the district where respondents reside in that same 30 day period. To capture the price effects of hot weather, we restrict our study period to warm season (March–November) and construct our central sample based on those respondents who reported the price regardless of having homegrown or purchased in the market consumption.[5] The 33,024 respondents in our central sample come from 21,984 rural and 11,040 urban households. With regard to the preferred temperature metric, the average maximum temperature is employed, defined to be the 30-day average of daily maximum temperature at the location of each respondent on the date in question. We further report findings based on other plausible temperatures (higher and lower temperatures).

Our study design allows for a clean identification as hot weather is exogenously determined. That is controlling for place and time the realization of heat metric is good as random. The results suggest that (a) a 1°C increase in average daily maximum temperature across the 30-day time frame causes a 0.66% increase in milk market price per litre in rural areas; (b) given other things equal the effect is more pronounced in non-poor households in both rural and urban India.

Our findings are robust to alternative specifications, including alternative heat metrics, clustering levels, and exclusion of outliers. The effect size from our preferred specification might not appear to be dramatic; however, accounting for the potential quantity required and consumed per day in these mostly large-sized households, the overall effect could be alarming.

We further investigate the effect of hot temperature on milk consumption concerning home-produced and purchased in the market consumption in rural and urban areas. We find evidence that temperature shocks disproportionately impact consumption depending on the household status.

Most prior literature concerning climate change and economic perspectives has correlated climate change to some agricultural outcomes such as crop productivity yields, agricultural production, land values, and farm profits, in the long run (Auffhammer and Schlenker, 2014; Hsiang, 2010; Schlenker and Roberts, 2009, 2006; Al et al., 2008). These studies found a broadly negative effect on agricultural production and productivity yield. However, the impact of weather variation on price volatility of dairy products is less established. In the present study, while we take advantage of literature on climate change-related agricultural productivity and profits as a valid baseline for a conceptual framework, we address a different economic aspect; the local price response to hot weather in the short term.

[5] Homegrown and purchased in the market will be discussed in section 1.7.

Our work contributes to the existing literature on the economic impact of climate change in several key ways: First, we examine the effect of a single event, hot weather, on the price, while previous empirical literature pointed to different types of climate change, including flooding and drought. Second, we investigate the local price impacts of hot weather faced by the households. The milk market is largely domestic, which limits the ability to compensate for reduced production in hot months and heatwaves. Also, the main driver for market prices for milk and dairy products could be the local conditions. Most of the existing literature on the nexus between climate change and economic impacts is focused at the national level and on long-term periods. However, the current study concentrates on the variation in local prices within the short-term (a sudden price spike) that could result in a more severe impact than a long-term price increase, which could be mitigated with appropriate coping actions.

We believe this to be the first attempt to test the reduced form causal relationship between hot weather and self-reported milk prices of a large sample of households with dispersion across a very broad set of districts in the short term (within-month). We owe this to a feature of our setting that provides us with detailed and disaggregated information that allows us to attain the local prices each household faces, the living circumstances of households, and whether they have homegrown or purchased consumption. Finally, unlike previous studies on climate change economic impacts that mainly concentrated on developed countries, our focus is a developing country: India.

Given the importance of price as a primary indicator of food security (Timmer, 2017), the plausible mechanism of price impact of hot weather can be explained as follows: First, agricultural productivity (here milk yield) can be affected by hot weather (ambient temperature of 29°C for dairy cattle)(West, 2003; Lees et al., 2019), and second, the lost production and physical damages combined with the supply chain's inefficient system would generate at least temporary deficiencies of dairy products and in particular of milk. Such shortages could, in turn, lead to swings in milk prices. Sussman and Freed (2008) argue that if food is not stored appropriately due to insufficient and inefficient storage infrastructure, the risk of food waste and contamination and food-borne diseases could increase. The situation becomes more crucial if the food is perishable and requires conditional or specific transportation and storage. This procedure can emerge not only significant health and economic losses but also can lead to a lack of supply, which is responsible mainly for food price increases. In our scenario, if this weather variation and the consequent price fluctuations become persistent, it could exacerbate the suffering of those who have already been affected directly by hot weather and distress other consumers. Milk price spikes thus could translate to higher expenses and aggravate the long-term consequences, particularly for low-income families (Dessus et al., 2008; Heinen et al., 2019).

Regarding the price determinants, not only do an economy's demand-supply conditions (non-weather determinants) impact prices in the agricultural sector, but so do variations in weather conditions. Such non-weather and observable factors include input quantity, population density, the proximity of settlement to farms and production centers, storage (cooling facilities, refrigerator), distribution, and logistics (Cervantes-Godoy and Dewbre, 2010; Fisher et al., 2012; Schlenker and Roberts, 2009). According to Cavallo et al. (2014), natural disasters attributed to climate change can lead to plausible supply and demand shocks that, in turn, can influence goods' productivity, availability, and prices. The supply shocks are associated with suppression of production capacity and malfunction of supply chains. Demand shocks, on the other hand, are linked to population density and consumers' way of thinking about a probable experience after a natural disaster. However, in this paper, the method applied and the nature of some data do not allow us to disentangle the potential supply- versus demand-side effects but instead solely investigate the reduced-form relationship between hot weather and milk's average market price.

The rest of the paper is structured as follows: Section 1.2 discusses the literature that highlighted milk's importance to health as well as the literature that examined the link between hot weather and adverse health and agricultural outcomes. Section 1.3 and 1.4 describe the data and the identification strategy. Section 1.5 and 1.6 present the empirical results and a series of robustness checks. In section 1.7, we have an overview on direct effect of hot weather on consumption. Section 1.8 concludes.

1.2 Literature review

Weather fluctuation is predicted to pose negative impacts on a variety of outcomes that have been well-documented in previous research. The effects have appeared in public health, agriculture, and economics literature. Hence, providing some relevant research is beneficial to shed light on several of the impacts induced by weather events.

1.2.1 Climate change and health impacts

According to the Lancet's Commission on Health and Climate Change, extreme weather is already impacting human health, and it is predicted that these impacts will continue to grow (Watts et al., 2018). A large body of literature connecting climate change to health effects targets the impacts that extreme heat weather and rising temperature could create for human health. For instance, heat events have been responsible for affecting people's life expectancy (Deschênes et al., 2009), neonatal and infant mortality (Banerjee and Maharaj, 2020; Geruso and Spears, 2018), premature death (Barreca, 2012; Burgess et al., 2017; Deschênes and Greenstone, 2011; Gasparrini et al., 2015), and low birth weight (Deschenes and Moretti, 2009; Grace et al., 2015).

Further, heat could cause children's cognitive impairment (Graff Zivin and Neidell, 2013; Park, 2017). Looking more closely at the myriad of adverse health effects aggravated by extreme heat and rising temperature, it appears that the impacts on some other principle outcomes such as malnutrition are less documented. Blom et al. (2019) assess the impact of lifetime and recent extreme heat exposure on chronic and acute nutrition measures for children aged 3-36 months in Africa. Their results reveal that lifetime exposure to temperatures above 35°C increases the prevalence of stunting by 10% and recent exposure to temperatures range between 30-35°C increases the prevalence of wasting by 16%. Such results have become of great concern as they can lead to crucial implications for human capital formation, cognitive functions, and economic growth in the long-run.

1.2.2 Climate change, agricultural and non-agricultural output, and price

Researchers have carried out considerable work on linking weather fluctuation to agricultural yields, land value, and profit. For example, Hsiang et al. (2017) use micro-level data to examine the linkage between the global mean surface temperature (GMT) and market and non-market costs across several sectors, including agriculture, in the United States. Their projections indicated that average national agricultural yields will decrease by approximately 9.1% for each 1°C that the global mean surface temperature increases.

In his earlier study, Hsiang (2010) estimates the impacts of temperature and cyclones on crop output in 28 Caribbean countries between 1970 and 2006. Using plausibly exogenous local year-to-year fluctuations in the weather, he found that unusually hot periods significantly reduce production, with losses of about 2.4% in non-agricultural output per 1°C increase. Productivity losses in mining and utilities, wholesale, retail, restaurants, and hotels, and other service-related industries are the primary drivers of these adverse impacts.

Schlenker and Roberts (2006) probe the reduced form association between weather and agricultural yields, focusing on corn yields in the eastern United States from 1950 to 2004. Their findings revealed a significant negative relationship between temperature and corn yields once the temperature exceeds 30°C. In line with their previous work, Schlenker and Roberts (2009) investigate the relationship between weather and three crucial agricultural products in the United States—corn, soybeans, and cotton—from 1950 to 2005. Their findings indicated while the output increases with temperatures up to 29°C, 30°C, and 32°C for corn, soybeans, and cotton, respectively, it will be adversely influenced once these temperatures exceed the given thresholds. They also suggested that the correct estimation of the association between weather and these crops' production is of great importance for investigating their supply and price response to climate change.

Quiggin (2007) examines the impact of drought on prices of fresh fruit and vegetable which are provided mostly by local producers for 2005 to 2007 in Australia and found 43% and 33% price increases for fresh fruit and vegetables, respectively. Diffenbaugh et al. (2012) assesse the impact of climate change on year-to-year corn price fluctuations in the United States and estimated the increase in U.S. corn-price volatility from 43% to 177% due climate change.

Further, Heinen et al. (2019) explore the effects of extreme weather on consumer prices in developing countries. Combining monthly data indices of hurricane and flood destruction in 15 Caribbean islands with consumer price data, they postulated that the price impact of extreme weather events could be considerable. Their findings suggested that one standard deviation (SD) increase in the hurricane index was associated with a 1.33 SD price increase. Also, a one SD increase for flooding led to a 0.12 SD price increase. Cavallo et al. (2014) investigate the impacts of the 2010 and 2011 earthquakes on product availability and prices in Chile and Japan, respectively. Using daily nationwide prices and a list of products obtained from the website of a large international retailer in each country, they compared the prices before and after the earthquakes and found that the goods' availability decreased by 32% and 17% in Chile and Japan, respectively. They also found that these deficiencies did not convert to higher prices and that prices were relatively stable.

Two additional studies that have touched on the link between temperature, agricultural outcomes, and food price are two case studies by Bandara and Cai (2014) and Arndt et al. (2012). Bandara and Cai (2014) study the impact of temperature changes on crop productivity, food prices, and food security on five large countries in South Asia, namely, Bangladesh, India, Nepal, Pakistan and Sri Lanka, using a global dynamic computable general equilibrium model. Their findings indicate that land productivity losses due to future climate change will lead to lower crop production and higher domestic food prices in the given countries. Similarly, in Tanzania, Arndt et al. (2012) by using historical daily climate data on the minimum and maximum surface temperatures and precipitation obtained from the NASA POWER database for 1997-2006, demonstrate that the reduction in agricultural products, mainly food production, is associated with temperature increases and rainfall patterns changes. Using sub-national crop models and a range of possible temperature and precipitation changes, they discuss that a decrease in agricultural production due to such changes leads to an increase in the consumer prices for agricultural products.

1.2.3 Milk importance to health

A growing body of scientific literature points out the importance of sufficient intake of milk and other dairy products to human health. Malnutrition induced by milk deficiency in daily diet is expected to have negative health impacts such as stunted growth in children. Multiple studies have found a significant relationship between milk intake and health outcomes. Dror and Allen (2011) found that when malnourished children consume milk and other animal-based food products, their ability to complete cognitive tasks increases and their morbidity and mortality decrease. In line with this result, Allen and Dror (2011) gave children milk supplements and compared them to a control group of children not given milk supplements, finding improvement in both the height and weight growth of the children who took the milk supplements. Likewise, Zhang et al. (2016) showed that in Zambia, adding even a slight amount of meat and milk to the poor households' diet notably increased their supply of nutrients such as protein, vitamin D, and calcium.

1.3 Data

In order to estimate the effect of hot weather on the price we construct a dataset from two components: Household survey data and the weather data.

1.3.1 Households

The primary data set is obtained from the India Human Development Survey-II (IHDS-II) in 2011–12, a multiple-subject survey with approximately 42,152 households in 1,503 villages, 971 urban neighbourhoods and 370 districts across India. The rural sample in IHDS-I was drawn using stratified random sampling and consists of the previously interviewed households in 1993-94 by the National Council of Applied Economic Research (NCAER). The urban sampling design was to select from a stratified sample of towns and cities within states, where the likelihood of dawning a unit is proportional to size. In IHDS-II, more than 80% of the sample was drawn from IHDS-I households being re-surveyed. The households being interviewed in the first wave of IHDS, though unable to locate the primary households, were replaced by a random sample of new households.

The IHDS is conducted by University of Maryland and NCAER, and its principal purpose is to provide researchers with nationally represented information on human development in India. To that end, the survey covers a broad range of topics in socioeconomic and health modules, including income, economic status, employment, education, agriculture, caste, religion, marriage, gender. The provided information has been applied in various example topics, including women's political autonomy (Carpena and Jensenius, 2021), children's human capital investment (Chari et al., 2017), and individual's economic performance (Heyes and Saberian, 2022).

Our outcome variable for the main specification is the reported milk market price driven from the households' responses to this question: "over the past 30 days, what was the average market price of one litre of milk?".[6] 41,825 (99%) of households answered to this question.

The IHDS-II is a multi-topic survey containing a rich set of control variables related to households, such as household size and financial status, their report on milk consumption in the past 30 days, and the status of consumption based on two sources, i.e., home produce and purchase. The database also covers the location of each interviewed household (state and district) as well as the interview date. Using the households district of residence allows us to merge the data from IHDS-II with what we know about temperature from the weather profile.

Ultimately, our central sample is constructed based on those respondents who reported the price regardless of having homegrown or purchased consumption. The 33,024 respondents in our central sample consist of 21,984 rural and 11,040 urban households.

1.3.2 Weather

India lacks adequate and reliable ground-based weather station networks to produce accurate weather data (Snyder et al., 2017). Following Alidoost et al. (2019); Auffhammer et al. (2020); Schlenker and Roberts (2009) we obtain our weather data from the ERA-Interim archive collected by researchers at the European Centre for Medium-Term Weather Forecasting (ECMWF).

Using ERA-Interim data, we are able to get maximum and minimum daily temperature, precipitation, and relative humidity records for 1°x 1°grid points for each day to map them with the interview period in IHDS data. As we are not aware of the exact address for each household, we use the district in which each household resides and apply an inverse-distance weighted average method for all the weather stations within 50 kilometres distance from centroid for each district,[7] to create weather variables corresponding to each district.

We then construct daily maximum and minimum temperature, rainfall amount, and rel-

[6] Question 14c on page 23 of Income and Social Capital Questionnaire

[7] An arbitrary maximum distance

ative humidity for each district on a given day. Our main results are based on the average maximum temperature, defined to be the mean of recorded daily maximum temperatures over the last 30 days prior to interview date at the household district Similarly, we take the aggregate rainfall and relative humidity over the 30 days before the interview date. We also include the number of days above 32°C, 34°C, and 38°C in each district in a 30-day window before the interview date to verify the robustness of our results.

Table 1-1 presents summary statistics of the data for about 33,024 households in our sample. Our main results rely on rural households, which construct more than 65% of India's population. Figure 1-1 plots the frequency of average daily maximum temperature over the past 30 days time frame, for March to November. Further, Figure 1-2 shows the association between price and temperature in the 30-day window. Visual demonstration suggests a positive linkage between the two variables.

1.4 Identification strategy

To study the causal link between hot weather and milk market price, we estimate the following specification:

$$Y_{itd} = \beta_0 + \beta_1 Temperature_{td} + \beta_2 W_{td} + \beta_3 H_i + \alpha_s + \gamma_t + \theta_y + \epsilon_{dit} \tag{1.1}$$

where Y_{idt} indicates the market price of one litre of milk that is reported by household i residing in district d over the past 30 days before the interview date t. $Temperature_{td}$ indexes the temperature measure, constructed as the 30-day average of daily maximum temperature following (Goodman et al., 2018). β_1 is the coefficient of interest.

W_{td} is a vector of non-temperature weather controls we include to allow for the likely impact of other weather factors such as rainfall and relative humidity. Also, H_i represents a set of controls for household characteristics, including the number of household members (household size) and income. The equation also contains α_s, indicating states fixed effect to control for the time-invariant heterogeneity across states (Schlenker and Roberts, 2009). γ_t and θ_y denote month and year fixed effects, respectively. Standard errors (ϵ_{idt}) are clustered at district level corresponding with the level at which the treatment variable (temperature) is assigned (Abadie et al., 2017).

To verify the robustness of our main findings, we later define the alternative level of clustering, and we show that the results are robust to the new calculations of standard errors. The identifying assumption throughout the present study is defined as when we control for place and month fixed effects, the realization of heat metric is good as random.

1.5 Main results

Our main results are presented in Table 1-2, indicating the impact of a 30-day average of daily maximum temperature prior to interview date as temperature regressor for rural India considering hot months (March-November). Column 1 presents the results given no controls but state, year and month fixed effects. The estimated coefficient on the treatment variable – temperature - is 0.1197, which is statistically significant at 5% level.

Progressing to the right end of the table, we add a set of weather controls such as rain sum and relative humidity (column 2) and household controls, including income and household size (column 3). The inclusion of weather and household controls in our regression improves the precision of our estimates.

In column 4, in addition to all of the above controls, we include the consumption status variable. That identifies the type of households consumption based on homegrown, purchase or both. The survey data concerning the status of consumption has many incomplete answers from the respondents, which lead to conducting the regression on a smaller sample (about 3,587 households). The estimated coefficient is positive and statistically significant (0.1604**).

Finally, column 5 reports the results from our preferred specification, in which we consider a complete set of controls and fixed effects though excluding the consumption status. The preferred specification design allows us to have our full sample of 21,984 for the rural area as the main focus, while the estimated coefficient is not much disturbed. Our coefficient of interest in this column is 0.1628, which is statistically significant at a 1% level.

Our explanatory variable, the average maximum temperature, is a simple 30 day mean of daily maximum temperatures, and the response variable is the household self-reported average milk market price for the past 30 days preceding the interview day. The estimated coefficient implies that 1°C increase in average daily maximum temperature over the 30 day time frame leads to a 0.17 Rupees increase in average milk market price per litre in rural India in hot months. When compared to the mean of 25.95, this translates into an effect of 0.7%.

Table 1-3 reports the results of re-estimating our preferred specification on the whole country, urban and rural subsamples. The 2011 Census of India indicates that the rate of urbanization is increasing, yet rural regions are still home to approximately 70% of Indians.

Evidence suggests that the effect is mainly driven by rural India when we probe the impact for the whole country.

In Table 1-4 both urban and rural regions are stratified into two subgroups by their reported income: poor is defined as very low income and non-poor as low and middle income. Findings are statistically significant for non-poor families in rural and urban regions; however, the results are more pronounced in rural India. Though it appears that the poor families should be the ones who report higher prices, evidence suggests that considering the weather and household controls, higher prices are reported by non-poor families. One degree C increase in average maximum temperature is associated with rising 0.23 and 0.13 Rupees in average milk market price per litre in rural and urban non-poor households, respectively.

1.6 Robustness

In this section we challenge the robustness of our main findings by re-estimating our preferred model applying alternative metrics for temperature (heat) and standard error.

1.6.1 Alternative heat metrics

Table 1-5 helps us to verify the robustness of our results applying alternative heat measures. In columns 2 through 4 we replace the treatment variable of interest (average daily maximum temperature) with different thresholds. That is when maximum temperature of that day exceeds 32°C (column 2), 34°C (column 3), and 38°C (column 4).

Although the estimated coefficients are smaller in value, the sign and significance are sustained, effects are positive and statistically significant at 5% level. That indicates, for example, the price per litre is 0.06 points (Rupees) higher when we have one extra day above the 32°C. When compared to the mean of 25.95 Rupees, this translates into an effect of 0.24%. The results in this table and findings from the primary specification reported in Table 1-2 evidence a positive and significant link between temperature and milk market price, regardless of the specific temperature metric applied.

1.6.2 Alternative standard errors

Our main analysis reported standard errors clustered at district level corresponding with the level at which the treatment variable is assigned (Abadie et al., 2017). Table 1-6 reports the results of re-estimating our main specification considering three alternative clustering approaches that might be of interest.

Column 1 presents the results of our preferred approach, which is clustering standard errors at the district level. In column 2, we show the results considering standard errors when unclustered and find no evidence of meaningful change in their effect size.

We also adopt state-year and state-month clustering approaches (Column 3 and column 4, respectively), following (Conley, 1999) study, which introduces higher spatial resolution of clustering for robust standard errors. We can observe that the results are significant and consistent with findings from our preferred clustering approach, suggesting that the reported price is not sensitive to the level of clustering adopted.

1.6.3 Outliers-Trimming and winsorizing

To investigate this possibility that a small number of outliers drives our estimated results, we perform two more exercises: trimming and winsorizing. These methods deal with possibly spurious outlier presence, which could affect the magnitude or direction of the coefficient and mislead the results. We replace an outlier value with the next highest to winsorize the data. We separately trim and winsorize at 5% for average daily maximum temperature and price. As for temperature, we consider the average daily maximum temperature <24°C and the average daily maximum temperature >45°C. Besides, milk price <10 Rupees and price >50 Rupees per litre are taken for trimming and winsorizing purpose after plotting their distribution. Results of temperature (treatment variable) trimming and winsorizing are presented in Table 1-7, column 1 and column 2. Also, columns 3 and 4 display the results from the outlier adjusting process for the dependent variable (milk price). With dependent and independent outliers winsorized and trimmed, the coefficients retain their direction and are statistically significant in both scenarios, discouraging the concern that extreme values influence the effect.

1.6.4 Rain

In all our specifications, we control for precipitation (rainfall) due to the potential role it might play in its own right. To probe this, we re-estimate our primary specification with regard to the amount of precipitation that households experienced at their location in the 30 days prior to their interview date, and we mainly focus on those days with the minimum level of precipitation.

Table 1-8 reports the results considering the non-monsoon season and dry days when precipitation is less than 1 mm (millimetre), 5mm, and 10mm. We observe that the coefficients' sign and significance are sustained though larger in value to some degree. In other words, we find no evidence suggestive of probable confounding effects of precipitation in our results.

1.7 Hot weather and consumption

We supplement our work by examining the household's consumption reaction to the hot weather. The IHDS dataset reports the households' monthly consumption of different food groups over the last 30 days, which could be purchased in the market, home-produced (home-grown), or both.[8] According to IHDS-II data, 76% of milk consumption comes from market purchasing, and 23% is based on consumption of the home-produced product. Most milk consumed in rural areas is purchased in the market rather than being home-produced. The number of households with both homegrown and purchased products is tiny compared to the two other categories, so we drop them. We re-estimate Equation 1.1 but with the dependent variable, milk market price, replaced by the milk consumption (litre) in the 30 days before the interview date. We then account for milk price as a control variable in the regression.

Table 1-9 presents the results considering urban and rural residency, combined with the economic status of households and the consumption status. We find evidence that families who have market-purchased milk consumption are those who bear the burden of heat, with effects being more pronounced for low-income families. For instance, the coefficient estimate on the category containing poor urban respondents, -0.6537***, indicates that, while controlling for other likely confounding factors, milk consumption decreases notably in households with purchased milk in the market. On the contrary, the estimated coefficients for rural families with homegrown consumption are positive though insignificant. That might be, in part, due to the income that households with homegrown milk earn by selling the milk in the market.

1.8 Conclusion

In this paper, we empirically investigate, as the first evidence, the causal association between average daily maximum temperature and milk's market price per litre. Using the India Human Development Survey-II in 2011–12 afforded us a rich, large-scale data set of households with micro-level data specific to each household and capture much detailed information on the households' economic status. In our main results, we consider the hot months (March–November) in India and analyze hot weather direct effect on milk market price.

Our findings suggest a highly significant relationship between hot weather and milk market

[8] Milk could not be purchased in PDS (public distribution system) shops

price. The average maximum temperature increasing by 1°C is significantly associated with milk's price increasing by 0.17 Rupees per litre in the rural sample. However, rural non-poor households are those who report higher prices owing to increased average maximum temperature. Results are robust to different heat metrics and clustering levels.

Although evidence shows that the expected price increase is on average small for the 30-day time frame, taking into account the potential quantity required and consumed per day in these mostly large-sized households with relatively many children, the overall effect would be considerable.

Using household data from India, we further probe the consumption implications due to hot weather for the 30 days before the interview date. We find evidence suggestive of a negative impact in both rural and urban areas; however, controlling for other likely confounding variables, milk consumption decreases significantly in poor urban households. With regard to the type of households consumption -home-produced and in-market purchased- we find evidence suggestive of potential pressure on households who meet their consumption needs from markets.

We can present the implications of our findings in different ways. Nonetheless, the ultimate concern could be poverty, food and health insecurity, which their pace of eradication would be slowed down due to weather events. Further, following Carty (2012), a sudden price hike could result in a more severe impact than a long-term price increase, which its impact could be mitigated with appropriate coping actions. More generally, our findings suggest that the potential short-term burden of price due to weather-induced milk shortages cannot be ignored, particularly for the poor, who are the most vulnerable to food inflation. While taking actions to reduce drivers of global warming, the government may require to develop social and economic protection plans targeted to assist the groups in need.

Table 1-1: Summary Statistics

	Mean	Std. Dev
Dependent Variable		
Milk average market price one litre (rupees)	25.95	8.48
Milk Consumption (Litres)	26.71	32.16
Independent Variable		
TmaxAvg (°C)	32.07	6.62
Hot days		
Days above 32°C	14.10	12.78
Days above 34°C	11.51	12.50
Days above 38°C	6.90	10.79
RainSum(mm)	136.35	267
Relative Humidity(%)	0.53	0.22
Income (rupees)	127759.8	216673.4
Household size (N)	4.85	2.32
Urban (%)	0.3457	0.4756

Notes: TmaxAvg indexes a 30 day average of daily maximum temperature.

Table 1-2: Main results - Average daily maximum temperature

	(1) No controls	(2) Weather	(3) Household	(4) Consumption	(5) Preferred
TmaxAvg	0.1197**	0.1624***	0.1167**	0.1604**	0.1628***
	(0.0554)	(0.0509)	(0.0549)	(0.0781)	(0.0501)
Weather controls	No	Yes	No	Yes	Yes
Household controls	No	No	Yes	Yes	Yes
Consumption control	No	No	No	Yes	No
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	21,984	21,984	21,984	18,397	21,984

Notes: Dependent variable is milk market price (Rupees) in the 30 days before the interview date. TmaxAvg defined as the 30-day average of daily maximum temperature before the interview. Results are presented for rural India for months March to November. Household controls contain the household size and income, and non-temperature weather controls include precipitation (rainfall) and relative humidity. Type of consumption refers to homegrown consumption or in-market purchased one. All regressions include state and month fixed effects. Standard errors are in parentheses and clustered at district level.
* p<0.1, ** p<0.05, *** p<0.01

Table 1-3: Main results - rural vs. urban

	(1) whole country	(2) Urban	(3) Rural
TmaxAvg	0.1174**	0.0965	0.1628***
	(0.0508)	(0.0677)	(0.0501)
Weather controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	33,024	11,040	21,984

Notes: Dependent variable is milk market price (Rupees) in the 30 days before the interview date. TmaxAvg defined as the 30-day average of daily maximum temperature before the interview. Results are presented for whole country, urban, and rural India for months March to November. Household controls contain the household size and income, and non-temperature weather controls include precipitation (rainfall) and relative humidity. All regressions include state and month fixed effects. Standard errors are in parentheses and clustered at district level. * p<0.1, ** p<0.05, *** p<0.01.

Table 1-4: Main results - Urban vs. rural
poor vs. non-poor

	Urban		Rural	
	(1)	(2)	(3)	(4)
	Poor	Non poor	Poor	Non poor
TmaxAvg	-0.0279	0.1317**	0.0395	0.2340***
	(0.1131)	(0.0643)	(0.0631)	(0.0476)
Weather controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,085	7,779	10,457	11,168

Notes: Dependent variable is milk market price (Rupees) in the 30 days before the interview date. The temperature metric is a 30-day average of daily maximum temperature. Results are presented separately for poor and non-poor households in urban and rural India for months March to November. Household. controls contain the household size and income, and non-temperature weather controls include precipitation (rainfall) and relative humidity. All regressions include state and month fixed effects. Standard errors are in parentheses and clustered at district level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 1-5: Alternative heat measures

	(1) Preferred	(2) >32°C	(3) >34°C	(4) >38°C
TmaxAvg	0.1628***			
	(0.0501)			
Days above 32°C		0.0612**		
		(0.0267)		
Days above 34°C			0.0682**	
			(0.0274)	
Days above 38°C				0.0617**
				(0.0311)
Weather controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	21,984	21,984	21,984	21,984

Notes: Dependent variable is milk average market price in the 30 days before the interview date. Columns (2) through column (4) repeat our preferred specification in column (1) but with the 30 day average of daily maximum temperature replaced by the number of days that maximum temperature at the interview location exceeds 32°C, 34°C, and 38°C, respectively, in the 30 days before the interview. See notes to Table 1-2 for the list of control variables. Results are presented for rural India for months March to November. Standard errors are clustered at district in parenthesis. * p <0.1, ** p<0.05, *** p<0.01.

Table 1-6: Alternative standard errors

	(1) District (preferred)	(2) Unclustered	(3) State-year	(4) State-month
TmaxAvg	0.1628***	0.1628***	0.1628**	0.1628***
	(0.0501)	(0.0148)	(0.0741)	(.0545)
Weather controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Number of Clusters	230	0	43	81
Observations	21,984	21,984	21,984	21,984

Notes: Dependent variable is milk average market price in the 30 days prior to interview date. TmaxAvg defined as the 30-day average of daily maximum temperature at the location of interview. Column (1) presents our preferred specification. Standard errors are unclustered in column (2), clustered at state-year in column (3), and state-month in column (4). See notes to Table 1-2 for the list of control variables. * p <0.1, ** p<0.05, *** p<0.01.

Table 1-7: Outlier analysis

		Temperature		Price	
	(1)	(2)	(3)	(4)	(5)
	Preferred	Trim	Winsorize	Trim	Winsorize
TmaxAvg	0.1628***	0.1311**	0.1518***	0.1732***	0.1656***
	(0.0501)	(0.0606)	(0.0577)	(0.0518)	(0.0496)
Weather controls	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	21,984	20,933	21,984	20,582	20,216

Notes: Dependent variable is milk average market price in the 30 days prior to interview date. TmaxAvg is the 30-day mean of daily maximum temperature at the location of interview. We separately trim and winsorize at 5% for TmaxAvg and Milk Price. For TmaxAvg we consider TmaxAvg <24°C and TmaxAvg>45°C. Also, we take milk price <10 Rupees and milk price > 50 Rupees for trimming and winsorizing purpose. See notes to Table 1-2 for the list of control variables. Standard errors are clustered at district in parenthesis.

Table 1-8: Rain

	(1) Preferred	(2) Non-Monsoon	(3) <1mm	(4) <5mm	(5) <10mm
TmaxAvg	0.1628***	0.1917***	0.2823***	0.2669***	0.2607***
	(0.0501)	(0.0581)	(0.0995)	(0.0922)	(0.0914)
Weather controls	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	21,984	13,487	3,563	8,108	10,716

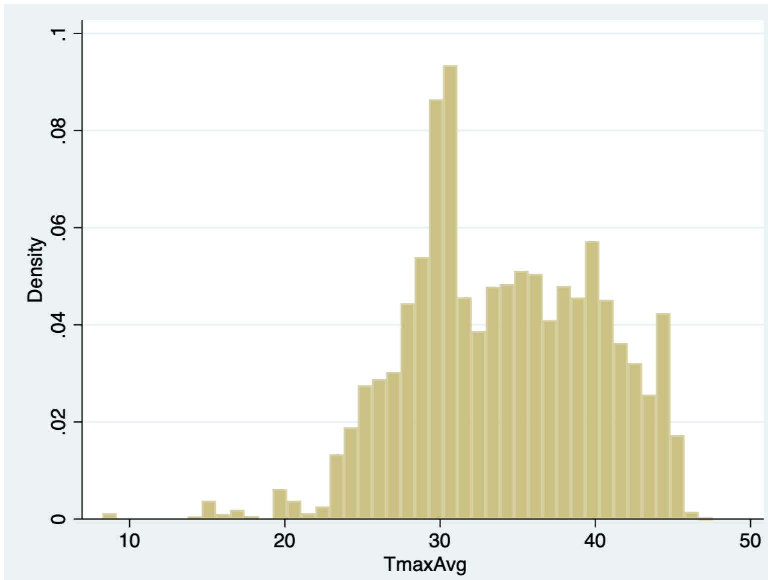
Notes: Dependent variable is milk average market price in the 30 days before the interview date. TmaxAvg defined as the 30-day average of daily maximum temperature before the interview. Standard errors are clustered at district in parenthesis. See notes to Table 1-2 for the list of control variables. Column (1) presents the results from our preferred specification. Columns (2) through (5) re-estimate the preferred specification considering non-monsoon season, days that average rainfall in 30 days before interview is less that 1 mm, 5mm, and 10mm, respectively. Non-monsoon season (summer/ hot) lasts from March to June. * p <0.1, ** p<0.05, *** p<0.01.

Table 1-9: Effect on consumption: Homegrown vs. purchased

	Rural		Rural		Urban	
	Homegrown		Purchased		Purchased	
	(1) Poor	(2) Non-poor	(3) Poor	(4) Non-poor	(5) Poor	(6) Non-poor
TmaxAvg	0.2032	0.2420	-0.3315**	-0.1581	-0.6537***	-0.2563
	(0.3694)	(0.3488)	(0.1409)	(0.1520)	(0.2704)	(0.1944)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,691	3,078	2,910	3,805	1,434	4,654

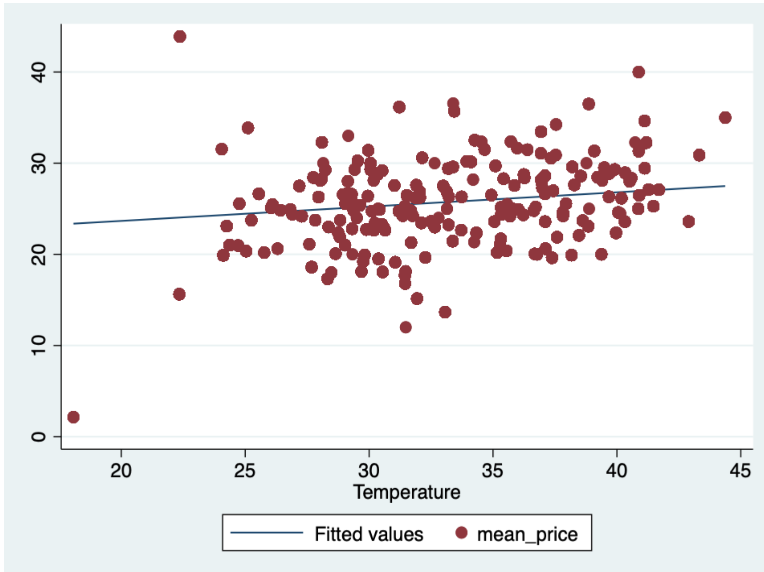
Notes: Dependent variable is milk consumption in the 30 days prior to interview date. TmaxAvg defined as the 30-day average of daily maximum temperature at the location of interview. Standard errors are clustered at district in parenthesis. See notes to Table 1-2 for the list of control variables. Milk price is also considered. Consumption is divided into home-produced and purchased in the market. For the urban area, due to very small number of observation for homegrown consumption, only consumption purchased in market is considered. For both the rural and urban regions, poor and non-poor households are considered.* p <0.1, ** p<0.05, *** p<0.01.

Figure 1-1: Temperature variation



Note: This figure plots the density of 30 days mean of recorded daily maximum temperature for March-November.

Figure 1-2: Price_Temperature



Note: The figure plots the association between average daily maximum temperature and average milk market price for March-November.

Chapter 2

Role of Education in Health-related Behaviours among Pregnant Woman in India

By Modjgan Alishahi

Abstract

Health-related behaviour and, in particular, attending antenatal care during pregnancy is essential to reduce the risk of pregnancy complications, stillbirth, and maternal mortality. This paper estimates the causal effect of years of formal education on the likelihood that a pregnant woman in India attends natal care and screening services. Despite the importance, insufficient documents exist on the determinants of natal care usage in developing countries. The current study investigates for the first time the hypothesis that women's schooling attainments might have a causal impact on natal care usage in India. Drawing on the nationally representative India Human Development Survey (IHDS-II) and instrumenting for years of schooling with plausibly exogenous variation in age at first menarche, we find that delayed age at menarche significantly increases formal education. Further, evidence suggests that an additional year of schooling significantly enhances the likelihood of uptaking the antenatal checkups. However, attending a sonogram/ultrasound does not appear to be significant.

2.1 Introduction

Maternal healthcare and, in particular, antenatal care is acknowledged to be central to a woman's well-being. It contributes to both mothers and their children's health by detecting and treating diseases and pregnancy-related complications, leading to reduced maternal morbidity and mortality.[1] Nevertheless, preventable and semi-preventable complications during pregnancy still influence mothers' and children's mortality in developing countries each year (Weitzman, 2017). Globally, about 800 women lose their lives due to pregnancy complications every day, and 20 percent belong to India.[2] Researchers have documented several barriers to seeking maternal health care (Ogbo et al., 2019).

Insights from Grossman's human capital model suggest that educational attainment as an input among several others in the health production function can lead to better health and health behaviours (Grossman, 1972). More educated people have been evidenced to be better producers of health compared to their less educated counterparts (Grossman, 1972; Chou et al., 2010; Lleras-Muney, 2005; Cutler and Lleras-Muney, 2010; Galama et al., 2018).

Women's elevated educational attainment can change their preferences and attitudes towards matters that impact their own and their offspring's health and well-being. That could be realized through impacting their health knowledge and beliefs regarding puberty, pregnancy, contraceptive methods, or pre-and post-natal care. Despite the need for education, according to a UNESCO report (2018),[3] 131 million primary school-aged girls are out of school. There are also 34 million female adolescents out of school, which leads them to miss the opportunity to learn essential skills and build knowledge; two-thirds of the 774 million illiterate people are female.

This paper probes the potential advantages of schooling regarding health-related behaviour among pregnant women. However, identifying the effects of education on our outcomes may be a challenge, as educational choices are often endogenous. Unobserved factors may remain that can contribute to both education and health behaviours even after controlling many observed variables.

We take the possible endogeneity problem of education to health behaviours into account and implement an Instrumental Variable (IV) strategy to overcome such issue. We investigate, for the first time, the hypothesis that women's schooling attainments have a causal

[1] https://www.who.int/publications/i/item/9789241549912

[2] https://www.unicef.org

[3] https://en.unesco.org/gem-report/sites/gem-report/files/girls-factsheet-en.pdf

effect on the likelihood that a pregnant woman in India attends natal care and screening services by instrumenting years of schooling with plausibly exogenous variation in age at first menarche.

Using the first menarcheal age appears to be relevant in India's context as many girls, owing to cultural and societal barriers,[4] drop out of school once they reach the menstruation age (Khanna, 2019). Timing of the first menarche can affect the age of marriage. Previous studies indicate that parents are willing to get their daughter married once she got menstruated to preserve her from having any pre-marital sexual experiences and to protect their family honor (Wahhaj, 2018). According to the UNICEF (2019), nearly 30% (223 million) of the globe's child brides live in India. among them 102 million were married before their 15th birthday.[5]

Early marriage may interrupt girls' formal education due to childbearing and family responsibilities (Carpena and Jensenius, 2021). In addition, many schools' poor sanitation infrastructure and less access to a safe and private space could also be problematic as a girl starting to menstruate. The available data shows that toilets are the missing infrastructure from many schools, and those with facilities do not necessarily have proper conditions for girls and boys separately. Such issue is more highlighted in government schools with about 40% of those lacking the toilet facilities (see Table 2-A.1). Such issues can expose girls to the risk of missing and dropping out of school.[6]

We draw on the India Human Development Survey (IHDS), a nationally representative data providing detailed information on health and socioeconomic and demographic information for 2011-2012. Using menarche age as an instrument for schooling, we find a significantly positive effect of years of schooling completed on the probability of undertaking routine tests, including uptaking any weight check, blood pressure, blood and urine test by 2.3 percentage points. The likelihood that a woman participates in any internal, abdomen, ultrasound, and amniocentesis check increases by 1 percentage point. Schooling increases the probability of attending any of these eight tests at least once during the last pregnancy by nearly 1.3 percentage points. A one-year increase in years of schooling completed increases the likelihood that a woman participates in weight check by 2.5 percentage points, a 2.8% increase over the sample mean of 0.868%, when we investigate the relationship between education and individual test uptake. However, investigating the impact of schooling on uptaking each test separately, we find no evidence that more years of schooling completed significantly raises

[4]Menstruation posits the menace of the reproduction period of a girl's life, which could exclude her from participation in religious practices or even restrict her mobility (Mahon and Fernandes, 2010).

[5]https://www.unicef.org/india/media/1176/file/Ending-Child-Marriage.pdf

[6]https://www.bbc.com/news/world-asia-india-58110935

the likelihood that women attend the ultrasound test.

This paper contributes to the existing literature on the association between human capital (measured by women's schooling) and health behaviour by highlighting that it is not only literacy itself that matters; years of formal schooling also matter. It examines the effect of years of formal schooling on attending a wide range of screening tests from simple blood pressure tests to ultrasound examinations by instrumenting the schooling attainments by menarche age.

Some previous literature utilized the menstruation timing to instrument for age at marriage (Chari et al., 2017; Dhamija and Roychowdhury, 2020; Field and Ambrus, 2008). However, to our knowledge, education instrumented by age at first menarche is novel in developing countries. Additionally, unlike other documents that created an index from pre-and post-natal health input (Chari et al., 2017), this study considers the impacts of education on several antenatal care types separately, in addition to variables which account for attending any antenatal care for the last pregnancy since 2005. That aims to show whether the years of schooling completed might affect the likelihood that pregnant women attend different check-ups tests. Moreover, this paper takes advantage of the IHDS, which is perfect with regard to providing data on age at first menstruation, combined with questions on pregnant women's characteristics and their maternal health-seeking behaviours.

We further probe heterogeneity across urban and rural India. We expect the impact of years of schooling to be smaller in the rural areas as better access to education in urban regions as well as exposure to different sources of information may lead to a more positive impact on women's propensity to uptake antenatal care. Although the impacts are statistically significant for both rural and urban residents, evidence suggests a more pronounced impact in urban areas. An additional year of formal schooling increases urban women's likelihood of attending any routine antenatal care by about 2 percentage points, compared with 1.1 percentage points for their rural counterparts.

The rest of the paper is structured as follows: section 2.2 provides an overview of the effect of education on health outcomes and health-related behaviours. Section 2.3 describes the data. Section 2.4 presents the identification strategy followed by a discussion on the related underlying assumptions in Section 2.5. Section 2.6 discusses the main results, and Section 2.7 provides robustness checks. Section 2.8 concludes.

2.2 Literature review

This section provides more in-depth insights into the importance of antenatal care and the link between education and health-related behaviour.

2.2.1 Importance of antenatal care

Antenatal care (ANC) as part of health-seeking behaviour among pregnant women is an opportunity to reduce morbidity and mortality associated with pregnancy both for mother and the children through diagnosis and treatment of some diseases and some pregnancy-attributed difficulties. It can happen through distinguishing girls and women with exposure to a higher risk of pregnancy and delivery complication (Carroli et al., 2001; Campbell et al., 2006). WHO reports that a lower rate of still birth has been observed among pregnant women who attended at least eight antenatal care visits.[7] Antenatal care uptaking coupled with delivery in a health facility lead to improve maternal health. Yet, in developing countries using such interventions is restricted (Say and Raine, 2007).

2.2.2 Education and health and health-related behaviours

According to Grossman (1972) human capital model, education serves as an input in the health production function to produce both health outcomes and health behaviours. Having completed more years of schooling plays a critical role in enhancing the overall health of society. Empirical studies on education have suggested striking correlations between education and health outcomes and health behaviours. Janke et al. (2020) probe the causal association between education and health conditions. Their findings reveal that except for diabetes, which is highly linked to lifestyle, the probability of other chronic illnesses falls with increased educational attainment. Using a natural experiment of universal primary education, Osili and Long (2008) suggest that an additional year of education reduces the number of births by 0.26 in Nigeria. Moreover, researchers have found that better-educated people tend to smoke less, consume less alcohol, exercise more, and have more frequent health check-ups (Cutler and Glaeser, 2005; Tansel and Karaoglan, 2016).

Cutler and Lleras-Muney (2010) examine possible explanations for the relationship between education and health behaviours, providing an essential account of education's role in promoting health behaviour through income, health insurance, and knowledge in the United States. Nevertheless, studies on schooling and health-related behaviours may suggest mixed

[7] https://www.who.int/news/item/07-11-2016-new-guidelines-on-antenatal-care-for-a-positive-pregnancy-experience

results. In other words, not all literature has found a positive and significant effect of education on health behaviour and health outcomes. Braakmann (2011) finds that the expansion of schooling in certain parts of England signifies no impact on various health-related measures nor an effect on health-related behaviour, e.g., smoking, drinking, or diet. Using regression discontinuity methods, Clark and Royer (2013) find no relationships between schooling and various health outcomes and health behaviours in the UK.

Although the studies are insufficient regarding maternal health-related behaviours and education, those that exist have indicated a positive causal association. For instance, Weitzman (2017) showed that improved women's education is linked to a decreased likelihood of short birth spacing and unwanted pregnancies, as well as enhanced antenatal healthcare utilization. Breierova and Duflo (2004), from an investigation of the causal effect of education on fertility and child mortality, suggest a strong causal impact of age at marriage and early pregnancy.

2.2.3 Age at first menarche and education

Researchers believe that the age girls reach menarche can affect their schooling years and consequent achievement. A small number of papers have begun probing the relationship between menarcheal age and education in girls, specifically in developing countries, and little is known about how this association occurs in practice.

Khanna (2019) examines the association between menarche age and school enrollment in India. Her findings indicate that reaching first menstruation before age 12 leads to a 13% school enrollment reduction. Another study conducted by Gill et al. (2017) suggest similar results. The authors probe the causal link between age at first menarche and the time spent in education using the meta-analysis findings of 57 studies for women of European descent. Their results indicate a statistically significant causal relation; women spend an extra 0.14 years (53 days) in school for every year delayed in age at menarche.

2.3 Data

We draw on the nationally representative India Human Development Survey (IHDS), a multi-topic survey of households across India. The IHDS was conducted with the cooperation of the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi. The rural sample in IHDS-I was drawn using stratified random sampling and consists of 13,900 rural households who were previously interviewed in 1993-94 by NCAER. The urban sample was selected from a stratified sample of towns and cities within states, where the likelihood of dawning a unit is proportional to size. With regard to IHDS-II, around 83% of the sample was obtained from IHDS-I households being re-interviewed. The households who were interviewed in IHDS-I, though they were not able to locate the primary households, had to be replaced with a random sample of new households.

IHDS-II interviewed 42,152 households, of whom 27,579 reside in rural India and 14,573 are urban dwellers. Households reside across 33 states and union territories, 384 districts, 1,420 villages, and 1,042 urban blocks in 276 towns and cities. The primary sampling unit (PSU) is formed from villages and urban blocks (150-200 households). The survey spans all states and union territories of India, except for the islands of Andaman/ Nicobar and Lakshadweep. The main objective of the IHDS is to provide data on human development in India, and it compasses a wide range of topics, including caste, religion, employment, household structure, education, and health.

The survey has household and individual questionnaires. The household questionnaire includes information on the family background such as caste, religion, urban/rural location, and economic status. The individual questionnaire contains detailed health and education information. IHDS (2011-12) presents a survey module called "Natal Care" where the eligible women (ever-married women aged 15-49) were asked whether they have had any antenatal check-ups in their last pregnancy since January 2005.

Our outcome variables throughout are obtained from the respondents' reports on antenatal checkups (Question 22.12 on Page 31). 28.7% of respondents provided an answer to this question. The data provides mainly dis-aggregated information on different types of health screening, including weight check, blood pressure, blood test, urine test, abdomen exam, sonogram/ultrasound, and amniocentesis.

Using the dis-aggregated information provided in the survey, we construct three dummy measures for antenatal checkups. The first measure is of form, Routine tests, a dummy variable taking value 1 if a woman attended any weight check, blood pressure, blood test, urine test, and zero, otherwise. The second measure, Checkup, will take value 1 if a woman has experienced any of the instances related to abdomen exam, sonogram/ultrasound, and amniocentesis. The measure Any test is similarly a dummy which takes value 1 if a woman attended any of these eight described tests and zero, otherwise.

The explanatory variables refer to the socioeconomic and demographic characteristics of women and their households, including age, place of residence (rural, urban), years of school completed, religion, caste (Brahmin, scheduled caste, scheduled tribe, other backward castes (OBCs)), parents' and siblings' education, and economic status. Among the respondents who provided an answer regarding education, 15,000 (38%) were illiterate (have no schooling). Other respondents reported having between one and 15 years of education.

We limit our sample to the ever-married women between the ages of 15 and 49 who have non-missing data for our outcomes (attending antenatal care test), excluding the respondents with zero level of schooling (illiterate respondents). That results in a final sample of 9,365 women. In our study, considering the girls who never enrolled in school is irrelevant. Summary statistics are presented in Table 2-1. Figure 2-1 plots the age at first menarche variation across respondents followed by schooling attainment distribution presentation (Figure 2-2).

2.4 Identification strategy

To explore the causal effects of education on health-related behaviours, the following regression is of our interest:

$$Y_{id} = \beta_1 Education_{id} + \beta_2 D_{id} + \gamma_d + \epsilon_{id} \tag{2.1}$$

where Y_{id} denotes health-related behaviours. $Education_{id}$ presents the years of schooling completed by woman i residing in district d. β_1 indicates our coefficient of interest which captures the effect of women's years of schooling completed on their health-relate behaviours. D_{id} is a vector of individual and household level controls, including woman's age, height, economic status, place of residence (urban/rural), caste, and father/husband's education. We also include district fixed effects (γ_d) to control for time-invariant district characteristics. Standard errors are clustered at the Primary Sampling Unit (PSU) level.

If education was exogenous and was unassociated with the error term, one could have interpreted the resulting association between our outcome and education as a causal link (Dhamija and Roychowdhury, 2020; Willage, 2018). That is, educational attainment could causally affect the probability of attending antenatal checkups. However, education is not randomly assigned, and the model can suffer from the endogeneity of women's education in the form of unobserved factors that can contribute to both education and health behaviours, such as nutrition. For example, as a leading cause of morbidity, poor nutrition may prevent girls from attending school or lead malnourished women to face several complications during pregnancy. Since nutrition affects both years of schooling and healthcare utilization, estimates of the effects of education on natal care attendance would be biased in such models. Hence, using a simple regression such as probability Linear Model (PLM), Logit, or Probit to understand the effect of years of schooling on our outcomes is not likely to be appropriate on account of endogeneity concerns.

To circumvent this issue, we follow Field and Ambrus (2008), Sekhri and Debnath (2014), and Chari et al. (2017), who employed plausibly exogenous variation in age at first menarche to instrument for age at marriage. However, we do not intend to consider age at marriage; rather, we use menarcheal age to predict educational attainment. In particular, we use an instrumental variable (IV) approach where the later menstruation is assumed to lead to more formal education. We create this variable as a binary which takes value 1 if the self-reported age at menarche is 13 or higher, zero otherwise.[8]

The IV approach involves estimating a two-stage regression to uncover the causal impact of education on health-related behaviour. The following first-stage regression (Equation 2.2) is estimated to test the hypothesis that age at menarche can significantly affect years of schooling in our sample even after controlling for all control variables. The equation is specified as follows:

$$Education_{id} = \alpha_1 AgeatMenarche_{id} + \alpha_2 D_{id} + \gamma_d + \epsilon_{id} \tag{2.2}$$

where *AgeatMenarch* is the instrument for individual's years of schooling, which takes value 1 if the individual's age at first menarche is 13 or older. Description of other variables are similar to Equation 2.1. In the first-stage, we predict the endogenous variable by using IV. That is, the endogenous variable (*Education*) is regressed on the instrument (*AgeatMenarch*).

In the second stage, the outcome variable is regressed on the predicted value of *Education* from the first-stage. In other words, the predicted endogenous variable from the first-stage will be used as the covariate in the following equation:

$$P(Y_{id} = 1 | \widehat{Education}_{id}, D_{id}) = logit(\beta_1 \widehat{Education}_{id} + \beta_2 D_{id} + \gamma_d + \epsilon_{id}) \tag{2.3}$$

Since our dependent variable is binary, it appears to be natural to interpret the expected value of Y_{id} as a probability or likelihood.

The validity of our IV approach rests on two assumptions. First, age at menarche must be correlated with years of schooling, even after considering controls. Second, age at first menarche must be associated with health-related behaviours only through education. We address these concerns in the section 2.5.

[8] The value for menarche age benchmark comes from the reported global mean.

2.5 Validity of instrument

Applying an IV approach to correct for the likely endogeneity of education requires the instrument to pass two conditions: relevancy and exclusion restriction.

2.5.1 Relevancy

The relevancy condition means that the instrumental variable should be able to explain variations in the endogenous variable of years of schooling completed, given that other related explanatory variables are being controlled.

Figure 2-3 and Figure 2-4 probe visually the association between age at menarche and level of education. The trends in the graphs illustrate the increase in average years of schooling completed for ages 12 years and older. The spike is more pronounced for urban dwellers. The positive trend provides evidence satisfying the first requirement.

Table 2-3 presents the results from first-stage regressions. Findings show that age at first menarche is a robust predictor of years of schooling completed. Particularly, we obtain a large F-statistic for age at menarche in all first-stage specifications. The F-statistic value greater than 10 from the first stage could confirm the absence of a weak instrument problem (Staiger and Stock, 1997). A one year increase in menarcheal age increases the years of schooling completed by 0.43 years (column 4).

2.5.2 Exogeneity and exclusion restriction

The exclusion restriction assumption indicates that the IV effects on the dependent variable should transmit only through the endogenous variable. This assumption requires the instrument to be uncorrelated with the error term. However, such an assumption cannot be directly tested. In our model, the exclusion restriction requires that age at first menarche, affects the health-related behaviours only through educational attainment.

There are few potential challenges to such an assumption that can increase the likelihood of a nonzero correlation between the instrumental variable and the error term. The exogeneity of the age at menarche, and the thought that the instrumental variable could pick up omitted factors such as age at first marriage (or delayed marriage) could be arguable in this regard. We discuss in what follows these challenges along with some explanations.

Biological literature on the determinants of the age of menarche reveals that genetic differences mainly drive variation in age at first menarche, and such genetic variation is a significant component of menarche timing (Kaprio et al., 1995; Campbell and Udry, 1995). For example, studying monozygotic and dizygotic twins, Kaprio et al. (1995) compare the correlation in menarche age across 1,283 twin pairs and find the correlation in first menarche age among monozygotic twins to be about three times larger than the correlation among dizygotic twins (about 0.21). Such evidence lends support to the menarcheal age randomness.

External influencers, such as nutrition, may still be of concern in the health context. One might argue that poor diet in early childhood could affect both the age at menarche, women's health and health-related behaviour in the long term (Karlberg, 2002). However, evidence from a systematic review of the relationship between age at first menarche and early-life diet patterns shows inconsistency across the world (Villamor and Jansen, 2016). Literature concerning nutrition and menarche nexus speaks to this intervening issue using height as a health measure. It is argued that stunting is a generic control for health/nutrition in early life. Based on the health information in IHDS data, and following Field and Ambrus (2008), Chari et al. (2017), and Sekhri and Debnath (2014), we control for the woman's height[9]as a proxy for early-life socioeconomic and health status.

If the height is a statistical measure for health, and if poor diet linked to menarche is severe enough to result in stunting, controlling for women's height can likely help to exclude any potential confounding factor attributing to health investment that can affect both menarche and our outcome variable (Chari et al., 2017). Results from Column 2 in Table 2-3 reports the coefficient of age at menarche after controlling for height (0.5325***). As can be seen, there is still a positive and significant link between school attainments and pubertal age. The inclusion of maternal height in the regression (first-stage) indicates slight changes in coefficient point estimate while the standard errors remain almost unchanged.

Additionally, first menstruation timing might be potentially endogenous to environmental factors such as rainfall and temperature. We follow Chari et al. (2017) and Field and Ambrus (2008) to minimize this issue by controlling for a geographical place of residence in childhood through including district fixed effect to account for spatial variation in exposure to environmental factors (column 4). The IHDS data includes only the information of women's current district of residence and not women's natal geographical location. Khanna (2019) and Fulford (2015) argue that most marriage in India occurs within the same district of the women's childhood residence; therefore, married women's current locality is likely the same as her natal district. Similarly, the results from Table 2-3 column 4 indicate that inclusion of district fixed effect in our specification, to control for variation in district-level factors, along with other controls, leads to a statistically significant coefficient (0.4306***). Findings confirm a

[9] In case of having information on Z-score, it would be an appropriate fit for showing health status. Yet, IHDS data does not include this information, and instead, it provides information on height and weight separately.

positive and significant relation between age at first menarche and school attainments.

With regard to the thought that the later menstruation could lead to delayed age at first marriage and the argument around the possibility of improved women empowerment within the household due to delayed age at marriage, it is noticeable that in India, age at marriage could be less of a concern as the minimum age at marriage is 18 years for women.[10] Despite some violations, parents often wait till their daughters turn 18 before entering the marriage market.

However, to address the concern of such a potential channel, two different exercises are presented. First, if delayed age at marriage could be a channel to positively impact the uptake of screening tests, then child marriage (marriage before age 18) while considering education could not improve health-related behaviour. Second, we consider the illiterate sample of women married at 18 years old and above to test whether this is only delayed marriage which affects the participation in screening tests. The findings from these tests lend support to the validity of our instrument.

In addition to the traditional instrumental variable approach, which is broadly applied and makes exclusion restriction assumptions, there are alternative strategies (e.g., those developed by Nevo and Rosen (2012) and Lewbel (2012)) that could be used when the valid external instrumental variable is challenged. For example, the instrumental variable approach developed by Lewbel (2012) identifies the effect of an endogenous regressor using a heteroscedastic covariance assumption. With regard to this approach and considering our model, β_1 in Equation 2.1 can be identified only based on the heteroscedastic distribution of the error term ϵ_{id} in the first-stage (Equation 2.2). This approach constructs a valid instrument for education (endogenous variable) using the information in the heteroscedastic distribution of the error term in Equation 2.2. Using the traditional IV approach to estimate β_1, we try to find a component of D_{id} (a vector of exogenous variables such as age, place of residence, and mother/ sister education) that appears in the first-stage equation but not in the Equation 2.1, and use this excluded regressor as an instrumental variable for education. The challenge regarding this method is that there might be no component of the exogenous regressors excluded from the Equation 2.1. Using the method by Lewbel (2012) helps to resolve the issue such that no components of the exogenous regressors can be used as an instrument for education.

[10]The Prohibition of Child Marriage Act 2005

2.6 Empirical results

This section presents the results from logistic regression, first- and second-stage estimations; however, our concentration for discussion is on the IV estimates.

2.6.1 Logistic regression

Table 2-2 provides the estimates of the effect of women's years of schooling completed on health-related behaviours (i.e. attending screening tests). These estimates do not indicate the causal link; nevertheless, they are likely to serve as a helpful baseline. Evidence suggests that one extra year of schooling completed is associated with an increase in the probability of women attending the routine screening tests by 1.7 percentage points, physical checkups attendance by 1 percentage point, and participating in any of the eight screening tests at least once by 1.1 percentage points. These effects are statistically significant at 1% level.

2.6.2 IV results

Table 2-3 presents the results from first-stage regression. The outcome variable throughout is years of schooling completed. Column 1 reports the results when education is regressed on age at menarche as our instrument for individual's years of schooling, which takes value 1 if the individual's age at first menarche is 13 or older, regardless of any control inclusion. Column 2 reports coefficient when just controlled for individual's height. The estimated coefficient is still positive and significant.

In column 3, an extensive set of household and individual characteristics, including the location of residence, mother's education, age, age squared, poor, religion, caste, and father/husband's education, are accounted for. The results meet our expectations with regard to direction and significance. Column 4 is the preferred specification in this table, and it is the same as that in column 3 but includes the district fixed effects to control for spatial factors. As evident the late age at menarche (age 13 or older) is positively and significantly related to education across all four specifications, highlighting the significant role of age at first menarche on years of schooling completed. The estimated coefficient in column 4 implies that late menarche leads to an extra 0.43 years of spending in school.

Our main results of IV regression are displayed in Table 2-4. It concentrates on the impact of years of schooling completed on the defined natal care checkups for the women aged 15-49 who had at least one birth following 2005. The table includes results in the form of marginal effects for three constructed measures. In the first column, a positive marginal effect of years of schooling suggests that women's schooling positively impacts the likelihood of attending the routine tests. In particular, one additional year of schooling completed leads to a 2.3 percentage points increase in the likelihood that a woman attend any screening test in the form of weight check, blood pressure, blood test, and urine test, at least once during her last pregnancy.

The estimated coefficient in column 2 implies that an extra year of schooling increases the likelihood of a woman attending any abdomen exam, sonogram/ultrasound, and amniocentesis at least once. The estimated coefficient is 0.0101, significant at 1% level of significance.

Column 3 reports the outcome of re-estimating the preferred specification for the third measure, Any test, by which we mean only on respondents who had attended any of the eight screening tests at least once. The results are consistent with the estimations in columns 1 and 2 in terms of significance and direction. An additional year of schooling completed leads to about 1.3 percentage points increase in the likelihood that a woman attends any type of screening tests at least once during her last pregnancy.

2.6.3 Urban-rural

This section provides results of probing the heterogeneity impact of place of residence. Around one-third of Indians are urban dwellers (31.2% in the 2011 census) and that is reflected in our sample (33.3% urban). Table 2-5 summarizes the results of conducting our preferred specification on the urban and rural sub-samples, respectively. With regard to direction and significance, estimations from urban and rural sub-samples show consistency with the main results, though as expected, the impact of years of schooling appears to be smaller in the rural areas as factors including better access to education in urban regions and exposure to different sources of information may lead to a more positive impact on women's propensity to uptake antenatal care. An additional year of formal schooling increases urban women's likelihood of attending any routine antenatal care by about 2 percentage points, compared with 1.1 percentage points for their rural counterparts.

2.7 Robustness

In this section, we challenge the robustness of our findings using several robustness check exercises.

2.7.1 Alternative estimation method

Our main results are obtained from the IV method with logistic regression; however, it is worthwhile to challenge the robustness of our results by employing an alternative non-linear strategy due to the dichotomous nature of our dependent variables. We re-estimate our preferred regression employing a Probit model (IV-Probit method), which uses maximum likelihood estimation by default following Tansel and Karaoglan (2016). The IV-probit coefficients are the change in the log odds of the outcome for a one-unit increase in the predictor variable. Since the log odds are challenging to interpret, we present the marginal effects instead of the log odds to suggest better interpretable estimates. The marginal effects offer the change in probability as the independent variable increases by one unit.

Results are presented in Table 2-6, showing consistency in sign and significance with findings from our preferred specification (Table 2-4), indicating that our results are robust to the choice of estimation method.

2.7.2 Alternative clustering

In this section we challenge the robustness of our main findings by re-estimating our preferred specification using alternative clustering strategies. Results are presented in Table 2-7. We opt district and state-year level for clustering following Conley (1999) study, which introduces a higher spatial resolution of clustering for robust standard errors. As can be observed, the results are consistent with the preferred clustering level, suggesting that the likelihood of attending the screening test is not sensitive to the level of clustering.

2.7.3 Linearity - Effect of age at menarche on years of schooling

This section discusses the possibility that the first stage relationship between age at menarche and schooling is linear. We follow the approach by Carpena and Jensenius (2021), though we instead carry out the regressions with regard to years of schooling completed rather than age at marriage. We show that our findings are robust to such a linear association. As seen in Table 2-8, the magnitude and significance of coefficients remain unchanged. We also provide the regressions for the IV first-stage in Table 2-A.2. Dependent variable is years of schooling completed. A one-year delay in age at first menarche increases the years spent at school by 0.10 years.

2.7.4 Additional exercise - Individual test

In many developing countries, health services do not reach everywhere uniformly. Therefore it would be of interest to probe the relationship between years of schooling and individual test/ checkup uptake. This practice would also serve as a robustness exercise, where it can be seen whether the primary association sustains across other specifications. The results are summarized in Table 2-9. The coefficients reported here are marginal effects obtained from IV regression using a logistic model similar to what we use for the main specification. As evident, coefficients are all positive and significant across the table. One year increase in education increases the probability of women attending the screening checkups. However, attending a sonogram/ultrasound appears to be insignificant.

One potential reason for such a result could be the restriction policies for using gender determination ultrasound, owing to the vast number of sex-selective abortions. Miller (2001) and Bhalotra and Cochrane (2010) discuss that features of Asian culture in support of son preference might be a leading factor for the prevalence of female fetuses abortion following the results of sex determination ultrasound. Further, Miller (2001) shows that having an older male sibling in the household decreased the likelihood of attending sex determination ultrasound. The cost factor has been identified as another probable reason for fewer ultrasound tests uptaking. Bhalotra and Cochrane (2010) argue though attending such checkups might not be very costly ($12, which equates to 1% of per capita income) due to highly skewed income distribution in India, it might result in a large burden for the poor households.

2.7.5 IV-Additional exercises

Table 2-10 reports the results of two additional exercises to discuss the robustness of our instrument. Column 1 presents the result from estimating our preferred model considering the full sample. Column 2 represents a sub-sample of women married before age 18 who have completed at least one year of schooling. As evident, the effect is positive and significant (about 1.1 percentage points) and not statistically different from the estimation obtained when using the full sample of women who have completed at least one year of schooling, indicating that education has a significant role to play in attending screening tests. Column 3 shows the result from using the sample of illiterate women whose age at first marriage is 18 and above. The coefficient is positive though insignificant (0.0034), stating that later age at marriage without education does not significantly improve the participation in screening tests.

2.8 Conclusion

Health-related behaviours and, considerably, uptaking antenatal care plays a critical role in reducing the risk of maternal morbidity and mortality and leading to mothers' and children improved wellbeing. This paper investigates whether there is a significant causal effect between women's years of schooling and their health-related behaviour during their last pregnancy in India. More specifically, we focus on attending eight types of checkups: weight check, blood pressure, blood test, urine test, abdomen exam, sonogram/ultrasound, and amniocentesis. To capture the causal association and overcome the education endogeneity challenge, we employ menarcheal age to reach exogenous variation in years of schooling completed. To our best knowledge, using menstruation age as an instrument for education is novel.

Using the 2011-12 IHDS data and two-stage regression, we find that every delayed year in menarcheal age is linked to an increase in the time spent in school. In other words, age at first menarche would be defined as a strong predictor for years of schooling completed. Further, applying IV regressions, we show that years of schooling completed is positively and significantly associated with the probability of women attending the routine tests, including uptaking any weight check, blood pressure, blood and urine test by 2.3 percentage points. The likelihood that a woman participates in any internal, abdomen, ultrasound, and amniocentesis check increases by 1 percentage point. Schooling increases the probability of attending any of these eight tests at least once during the last pregnancy by nearly 1.3 percentage points. A one-year increase in years of schooling completed increases the probability of a woman participates in weight check by 2.5 percentage points, a 2.8% increase over the sample mean of 0.868%, when we investigate the relationship between education and individual test uptake. However, investigating the impact of schooling on uptaking each test separately, we find no evidence that more years of schooling completed significantly raises the likelihood that women attend the ultrasound test.

Our findings highlight the relevance of policies that seek to raise public awareness regarding the pregnancy-attributed risk that would affect mothers' and children's health and wellbeing, through improving education. Further, the policies that seek to establish social equity concerning the availability and distribution of health facilities that provide affordable medical assistance are required.

Figure 2-1: Pubertal age distribution .

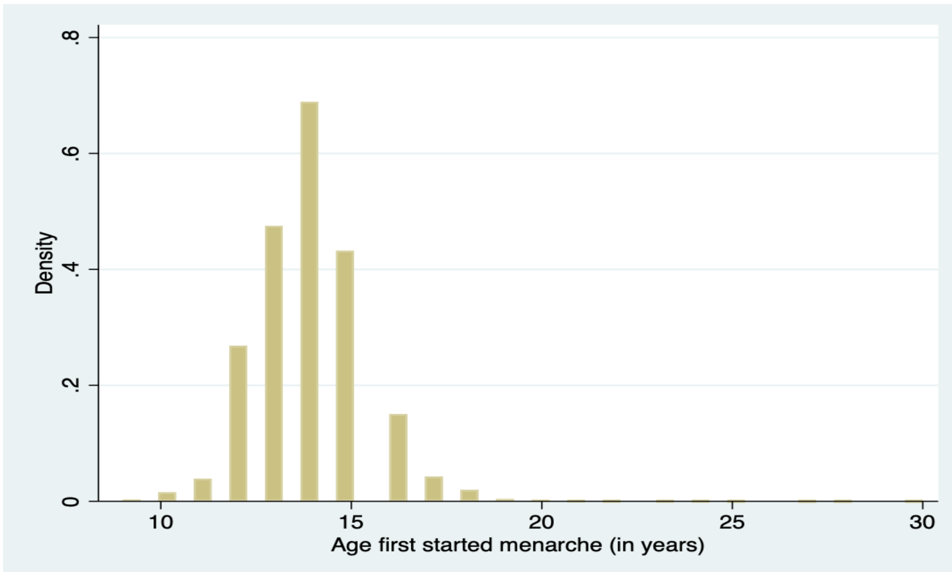


Figure 2-2: Schooling attainment distribution

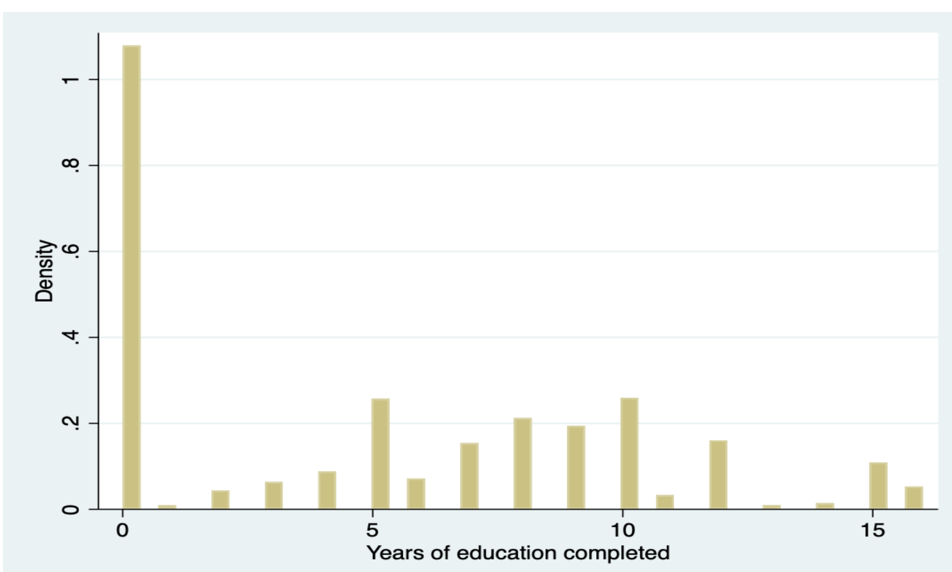


Figure 2-3: Education and Age at Menarche (Urban area)

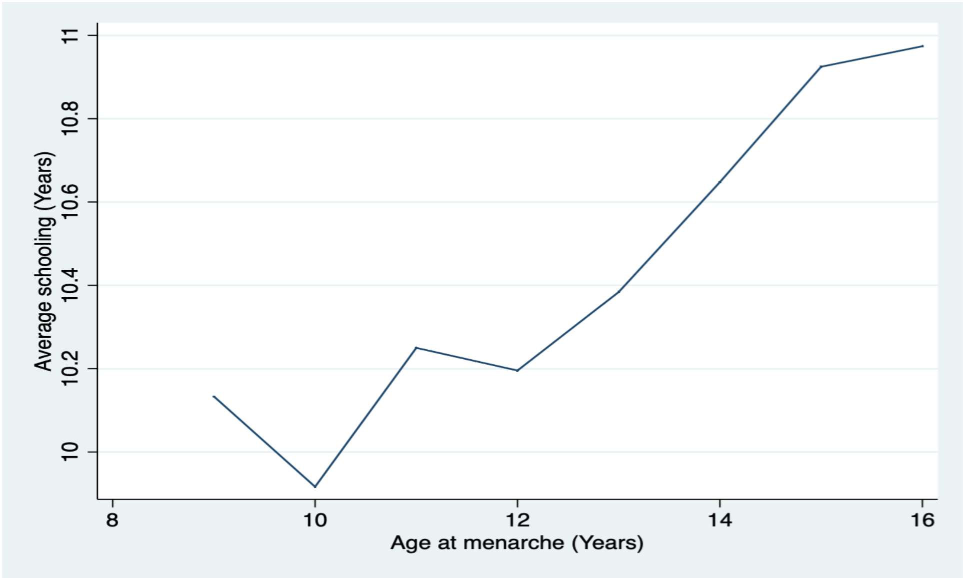


Figure 2-4: Education and Age at Menarche (Rural area)

Table 2-1: Summary Statistics

	Mean	Std.Dev.
Woman Demographic Characteristics		
Years of schooling completed	6.767	4.890
Age at first menarche	13.881	1.459
Age	28.164	5.381
Height(cm)	151.802	8.598
Sister's education (years)	6.880	5.280
Father/Husband education	2.560	3.818
Hindu (%)	81.74	-
Muslim (%)	11.67	-
Households characteristics		
Household size	5.615	2.730
Urban	0.333	0.471
Poor	0.232	0.422
Screening tests		
Weight check	0.868	0.338
Blood test	0.840	0.366
Blood pressure	0.865	0.341
Urine test	0.864	0.342
Abdomen	0.862	0.344
Internal	0.513	0.499
Ultrasound	0.622	0.484
Amniocentesis	0.168	0.374

Notes: Descriptive statistics are presented for eligible women aged between 15 and 49 who at least have one year of schooling completed and participated in at least one antenatal checkup.

Table 2-2: Effect of education on health-related behaviours

	Dependent Variable		
	(1) Routine test	(2) Checkup	(3) Any test
Years of schooling	0.0168***	0.0101***	0.0115***
	(0.0011)	(0.0015)	(0.0010)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	9,365	9,365	9,365

Note: The table presents the results (marginal effects) of logistic regression in which the dependent variables are binary across all specifications. Routine test in Column 1 defines attending any weight check, blood pressure, blood test, and urine test at least once during the last pregnancy. Checkup (Column 2) refers to attending any abdomen exam, internal exam, sonogram/ ultrasound, and amniocentesis. Any test(column 3) refers to attending any of screening tests at least once. All dependent variables are binarized as 1 if a woman attends the test at least once and 0 otherwise. Controls include urbanity, sister's education, father/husband education, age, economic status, religion, and caste. District fixed effects are also considered. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-3: Effect of age at menarche on education - First stage

	Years of schooling completed			
	(1)	(2)	(3)	(4)
Age at menarche	0.6105***	0.5325***	0.4108***	0.4306***
	(0.1582)	(0.1575)	(0.1371)	(0.1093)
Controls				
Household Controls	No	No	Yes	Yes
Individual Controls	No	Yes	Yes	Yes
District FE	No	No	No	Yes
F-Test	14.88	62.34	213.45	116
Observation	9,365	9,365	9,365	9,365

Notes: The table shows the results of the first-stage regression. The outcome variable is years of schooling completed. Column (1) reports the coefficient of interest without including any additional controls. Column (2) considers the women's height (from individuals characteristics) as a control. Column (3) contains all households and individual controls including urbanity, sister's education, father/husband education, age, age squared, economic status, religion, and caste. In Column (4), in addition to the full set of controls, we add district fixed effects. F-statistic for strength of the IV is reported across the table. Robust standard errors are in parentheses and clustered at PSU (village/neighbourhood) level . Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-4: Main results - Marginal effects

	Dependent Variable		
	(1)	(2)	(3)
	Routine test	Checkup	Any test
Years of schooling	0.0229***	0.0101***	0.0125***
	(0.0021)	(0.0009)	(0.0010)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	9,365	9,365	9,365

Note: The table presents the results of IV regression using a logistic model in which the dependent variables are binary across all specifications. Routine test in Column 1 defines attending any weight check, blood pressure, blood test, and urine test at least once during the last pregnancy. Checkup (Column 2) refers to attending any abdomen exam, internal exam, sonogram/ ultrasound, and amniocentesis. All dependent variables are binarized as 1 if a woman attends the test at least once and 0 otherwise. Column 3 contains attending any of the screening tests. See notes to Table 2-3 for full list of controls. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-5: Main results - Urban vs. rural

	(1) Routine test	(2) Checkup	(3) Any test
Panel A: Main			
Years of schooling	0.0229***	0.0101***	0.0125***
	(0.0021)	(0.0009)	(0.0010)
Observations	9,365	9,365	9,365
Panel B: Urban			
	(1)	(2)	(3)
	Routine test	Checkup	Any test
Years of schooling	0.0196***	0.0118***	0.0150***
	(0.0015)	(0.0014)	(0.0015)
Observations	3,190	3,190	3,190
Panel C: Rural			
	(1)	(2)	(3)
	Routine test	Checkup	Any test
Years of schooling	0.0115***	0.0072***	0.0098***
	(0.0014)	(0.0012)	(0.0013)
Observations	6,175	6,175	6,175
Household controls	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
District FEs	Yes	Yes	Yes

Note: The table presents the results of IV regression for urban and rural areas separately. See notes to Table 2-3 for full list of controls and dependent variables description. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-6: Robustness - Marginal effects

	Dependent Variable		
	(1) Routine test	(2) Checkup	(3) Any test
Years of schooling	0.0125***	0.0094***	0.0106***
	(0.0008)	(0.0007)	(0.0019)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	9,365	9,365	9,365

Note: The table presents the results of IV regression using a probit model in which the dependent variables are binary across all specifications. See notes to Table 2-3 for full list of controls and dependent variables description. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-7: Alternative clustering

Panel A: Preferred - PSU			
	(1)	(2)	(3)
	Routine test	Checkup	Any test
Years of schooling	0.0229***	0.0101***	0.0125***
	(0.0021)	(0.0009)	(0.0010)
Observations	9,365	9,365	9,365
Panel B: District			
	(1)	(2)	(3)
	Routine test	Checkup	All tests
Years of schooling	0.0229***	0.0101***	0.0125***
	(0.0012)	(0.0010)	(0.0011)
Observations	9,365	9,365	9,365
Panel C: State and year			
	(1)	(2)	(3)
	Routine test	Checkup	All tests
Years of schooling	0.0228***	0.0101***	0.0125***
	(0.0017)	(0.0008)	(0.0008)
Observations	9,365	9,365	9,365
Household controls	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
District FEs	Yes	Yes	Yes

Note: The table presents the results of IV regression. Dependent variables are binarized and related to health behaviour. See notes to Table 2-3 for full list of controls and dependent variables description. Panel A shows our preferred specification. Panels B and C present standard errors clustered on district and state-year, respectively. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-8: Robustness to using age at menarche - linearity

	Dependent Variable		
	(1) Routine test	(2) Checkup	(3) Any test
Years of schooling	0.0239***	0.0112***	0.0115***
	(0.0021)	(0.0009)	(0.0011)
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	9,365	9,365	9,365

Note: The table re-estimates the IV regression in Table 2-4 but considers age at menarche as an instrument to consider linearity and not the binary variable for menarche. Dependent variables are binary across all specifications. Routine test in Column 1 defines attending any weight check, blood pressure, blood test, and urine test at least once during the last pregnancy. Checkup (Column 2) refers to attending any abdomen exam, internal exam, sonogram/ ultrasound, and amniocentesis. Column 3 contains attending any of these eight tests. All dependent variables are binarized as 1 if a woman attends the test at least once and 0 otherwise. See notes to Table 2-3 for full list of controls. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-9: Results for individual test

	Dependent Variable							
	(1) weight check	(2) blood pressure	(3) blood test	(4) urine	(5) abdomen	(6) internal	(7) ultrasound	(8) amniocentesis
Years of schooling	0.0245***	0.0184***	0.0175***	0.0192***	0.0107***	0.0104***	0.0134	0.0101***
	(0.0034)	(0.0012)	(0.0011)	(0.0013)	(0.0037)	(0.0013)	(0.0761)	(0.0015)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	9,367	9,367	9,365	9,365	9,365	9,365	9,365	9,343

Notes: IV estimates. The dependent variables are different types of antenatal care screening test during pregnancy and are binarized as 1 if a woman attends the checkups test at least once, and 0 otherwise. The coefficients are marginal effects. See notes to Table 2-3 for full list of controls. Robust standard errors in parentheses and clustered at PSU level. Significance at * p<0.1, ** p<0.05, *** p<0.01.

Table 2-10: IV-Robustness check

	(1) Full sample	(2) Age at first marriage <18	(3) Age at first marriage 18+
Any test	0.0125***	0.0117***	0.0034
	(0.0010)	(0.0030)	(0.0065)
Education	Yes	Yes	No
Individual controls	Yes	Yes	Yes
Household controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	9,365	3,863	1,806

Notes: The dependent variable defines attending any weight check, blood pressure, blood test, urine test, abdomen exam, internal exam, sonogram/ ultrasound, and amniocentesis at least once during the last pregnancy and is binarized as 1 if a woman attends the checkups test at least once and 0 otherwise. See notes to Table 2-3 for full list of controls. Column 1 presents the result from our preferred model considering the full sample. Column 2 represents a sub-sample of women married before age 18 who have completed at least one year of schooling. In column 3, the sample of illiterate women whose age at first marriage is 18 and above is considered. Robust standard errors in parentheses and clustered at PSU level. Significance at * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

2-A Appendix

Table 2-A.1: School toilet facility for the students

	Type of School	
	(1) Government	(2) Private and other
School has toilet	0.6091	0.7831
	(0.4880)	(0.4121)
Observation	2029	1748
School has separate toilet (girls)	0.7530	0.7926
	(0.4210)	(0.4053)
Observation	1236	1369

Note: Data obtained from IHDS-I, 2005. Standard errors in parenthesis.

Table 2-A.2: Effect of age at menarche on education - Linearity

	Years of schooling completed			
	(1)	(2)	(3)	(4)
Age at menarche	0.1228***	0.1066***	0.0940***	0.1027***
	(0.0399)	(0.0393)	(0.0341)	(0.0264)
Controls				
Household Controls	No	No	Yes	Yes
Individual Controls	No	Yes	Yes	Yes
District FE	No	No	No	Yes
F-Test	17.11	60.38	212.30	115.09
Observation	9,365	9,365	9,365	9,365

Notes: The table shows the results of the first-stage regression considering linear relationship between age at menarche and years of schooling. The outcome variable is years of schooling completed. Column 1 reports the coefficient of interest without including any additional controls. Column 2 considers the women's height. Column 3 contains all households and individual controls including urbanity, sister's education, father/husband education, age, economic status, religion, and caste. In Column 4, in addition to the full set of controls, we add district fixed effects. F-statistic for strength of the IV is reported across the table. Robust standard errors are in parentheses and clustered at PSU (village/neighbourhood) level . Significance at * p<0.1, ** p<0.05, *** p<0.01.

Chapter 3

Adolescent Girls Empowerment Policy, Health Awareness, and Decision Making : Evidence from SABLA Program in India

By Modjgan Alishahi & Samira Hasanzadeh

Abstract Adolescent girls are amongst the vulnerable groups exposed to the risks that challenge their healthy development into young women. India's Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (SABLA) program was designed to address such challenges by building health awareness and encouraging decision-making autonomy as the first steps towards real change in women's development. Using data from the nationally representative India Demographic and Health Survey (IDHS), with plausibly exogenous variations in the program's rollout across districts and birth cohorts, we provide evidence that exposure to SABLA increases the likelihood of having knowledge of family planning and diarrhoea treatment, using contraception, and autonomy in personal financial decision-making for exposed women. The effects are more pronounced for women residing in urban areas, for women who have secondary education or higher, and primarily for Muslim women.

3.1 Introduction

Women empowerment can cause economic development (Duflo, 2012). Enhancement of women's health and socioeconomic status, including increased awareness concerning their own and their children's health and improved autonomy in decision-making, can impact every dimension of development. A vast strand of literature on development investigates women's empowerment from different socioeconomic aspects, yet the role of adolescence as a developmental phase in the life span has been less explored (Currie and Alemán-Díaz, 2015).

Adolescence, as a transitional episode from childhood to adulthood, can form ideas and beliefs, enhance life skills, and can shape the capabilities an individual can take forward into adult life. These capabilities are among the various methods leading to empowering women (Sawyer et al., 2018; Banseria et al., 2019). On the other hand, adolescent girls are exposed to a range of susceptibilities due to harmful social norms affecting females' rights, which could impact their capabilities to participate in decision-making activities regarding their health, education, marriage and social relationships (Bearinger et al., 2007; George et al., 2020). Evidence of positive effects has made the growth of using empowerment programs an acceptable path to achieve well-being and play a role in decision-making (Stuckelberger, 2010; Chaudhuri, 2013). Given the critical role of such outcomes in human capital formation, understanding the effect of empowerment program introduction may have significant implications for public policy and household behaviours.

In this paper, we evaluate the impact of introducing a multidimensional intervention in late 2010 in India, India's Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (RGSEAG)- SABLA. The objective of the scheme was to raise awareness on health and health behaviours, and to promote self-development and life skills, targeting adolescent girls aged 11-18 (Vista and Bhav, 2013). We show how family planning knowledge, use of family planning methods (contraception), autonomy in decision-making, and knowledge of infectious disease treatment, respond.

We exploit plausibly exogenous variation generated by the geographic-wise rollout of the program coupled with the variation in cohort eligibility (birth cohort). As the SABLA program was implemented across different districts and includes women of ages 11-18 solely, we can identify the effects of SABLA by comparing women's outcomes across cohorts within a given district and across districts with and without the program implementation. This difference-in-differences approach allows us to estimate the effect of potential SABLA exposure on adolescent girls' outcomes while holding constant fixed characteristics of districts and birth cohorts that might affect their outcomes and might also be correlated with the program introduction.

India serves as an ideal setting in our investigation. With approximately 253 million adolescents, India ranks one in the world in terms of the young population. Every fifth person in India is an adolescent (10-19 years), and every third person between 10 to 24 years is considered young. Additionally, according to the National Family Health Survey (NFHS-IV) analysis, 7.9% of females aged 15-19 years had children or were pregnant at the time of the interview. According to a UN report (2013), the economic burden of $7.7 billion a year (amounted to nearly 12% of the country's GDP) was borne by the country owing to teenage pregnancies. Moreover, diarrhoea has been recognized as a leading cause of mortality among children under five years old in India. Ghosh et al. (2021) discussed that despite implementing several programs targeting to control the disease and reducing the associated mortality in India, diarrhoea-related mortality is still alarming. A considerable proportion of such deaths are associated with dehydration, delayed treatment or mismanagement of disease. Nevertheless, knowledge in managing/ treating such morbidity can help treat this problem at home.

To carry out our analysis, we use data from a 2015-16 survey of India Demographic and Health Survey (IDHS), referred to as the National Family Health Survey (NFHS).[1] The data includes socioeconomic and health characteristics of over 699,686 eligible women (aged 15-49) with several detailed information on their individual and household characteristics, including age, educational attainment, number of household members, living children, current work status, wealth index, place of residence, caste, and religion. Our focus is on the information provided by ever-married women under fertility and fertility preferences, and family planning survey modules.

We present evidence based on the intent-to-treat (ITT) concept following Gentzkow and Shapiro (2008), supporting the hypothesis that exposure to empowerment programs improves the socioeconomic and health outcomes of adolescent girls. More precisely, our estimates from the preferred model suggest that potentially exposed women to the program are more likely (about 1 percentage point) to know about family planning methods than those not exposed. We also find that exposed women are 9.5 percentage points more likely to have autonomy in controlling over their money than those not exposed to the program, suggesting potential enhancement in their bargaining power in the household. In addition, results provide evidence that exposed women to the policy are 0.5 percentage points more likely to know about

[1] For simplicity we use IDHS throughout this document

infectious disease (diarrhoea) treatment.

Our findings are robust to alternative specifications and exercises, including applying intensity of exposure to the program, controlling for another confounding control variable, alternative cohort upper bound, different levels of clustering, and conducting a placebo test. We additionally perform a randomization test to probe the identifying assumption that the introduction of SABLA is uncorrelated with individual and household level characteristics at the district level, ensuring that the SABLA program was not endogenously assigned to the districts. We find that none of the coefficients appear to be significant, suggesting that treatment assignment is not systematically linked to district-specific characteristics.

The final set of our findings addresses heterogeneity in the impact of the program implementation on our outcomes. The effects on having knowledge of family planning and diarrhoea treatment, using contraception, and autonomy in personal financial decision-making are more pronounced for women residing in urban areas, women with secondary education or higher, and for Muslim women.

Our results point toward an essential economic intuition that the program seems to be most beneficial for relatively advantaged women in terms of place of residence and educational attainment. For women with no or primary education and those who lived in rural areas, the effects of the SABLA program appear to be smaller and may even be negative. Such results can cast doubt on intervention programs such as SABLA that mainly targeted advancing the rural women empowerment status.

Our study contributes to an extensive literature on the health and socioeconomic effects of women empowerment programs, most of which identify the effect of such programs on fertility, employment, and violence. Although closely linked, they differ from ours. It additionally contributes to a growing economic literature on the effects of informal education on a broad set of indicators of women empowerment, including health awareness and attitudes toward healthy behaviours, such as reproductive behaviour (family planning) and decision-making. To our knowledge, this paper provides the first causal analysis of the efficacy of an adolescent girls empowerment program on such a broad range of empowerment indicators.

The remainder of this chapter is structured as follows. Section 3.2 overviews the existing relevant literature. Section 3.3 discusses the policy background. Section 3.4 presents our data for the analysis, and Section 3.5 outlines our empirical strategy and reduced-form results. The estimation results then appear in Section 3.6, and section 3.7 presents an analysis of heterogeneity across women. Section 3.8 reports the findings from several robustness exercises. Section 3.9 concludes.

3.2 Literature review

The empirical literature on gender-targeted policies and women empowerment ranges widely from studies focusing on women's access to employment and economic sources (such as cash transfers) (Rodriguez, 2022; Pettifor et al., 2016; Baird et al., 2010; Velasco et al., 2020), to research considering women's age at marriage and reproductive health rights and behaviours (Joshi and Schultz, 2013; McGavock, 2021; Clarke and Mühlrad, 2021) to literature centring on education and training (Duflo et al., 2015; Kandpal et al., 2012). These studies often vary according to their contexts, as women empowerment is mainly concerned with the differences in social norms across societies and how these norms affect household insights into development.

For instance, McGavock (2021) argues that Ethiopia's child marriage law (in 2000), which aimed to raise the minimum age of girl's marriage from 15 to 18, helped to decrease the likelihood of involving a girl under age 16 in marriage. In terms of education subsidy programs and women's health and socioeconomic outcomes, Duflo et al. (2015) posit that such programs curbed the school dropout rates of adolescent girls and reduced the incidents of marriage and pregnancy. Kandpal et al. (2012) find that providing literacy camps, adult education classes and vocational training to women can increase their mobility, political participation and access to employment.

In another piece of evidence within the area of women empowerment, Hewett et al. (2021) evaluate a nutritional educational intervention tailored for adolescent girls in Zambia focused on nutritional knowledge and dietary behaviour. Their findings indicate that exposure to these types of programs did not significantly influence adolescent girls' nutritional knowledge and dietary behaviours. In Bangladesh, a well-known maternal and child health and family planning program, offered in 1977, was observed to reduce child mortality, enhance women's health and the use of preventive health inputs, such as the average number of antenatal visits per pregnancy for all of a woman's pregnancies (Joshi and Schultz, 2013).

This paper contributes to the avenues for research on the effectiveness of such gender-targeted and empowerment policies in another domain of women empowerment, including knowledge of family planning, infectious disease management, and decision-making.

3.3 Rajiv Gandhi Scheme for Empowerment of Adolescent Girls (RGSEAG)-SABLA

The Rajiv Gandhi Scheme for Empowerment of Adolescent Girls, SABLA, a program introduced in late 2010, is a cross-country multidimensional empowerment policy initiated by the Government of India under the Ministry of Women and Child Development and the Integrated Child Development Services (ICDS), which aims to empower adolescent girls (AGs) in all states and union territories in 200 selected districts on a pilot basis.[2] The scheme had been an ongoing project for the given district since its implementation. However, the government has expanded this scheme to a total of 508 districts in 2017-18.[3]

The selection criterion for the districts relied on the combination of good, moderate and poor performing districts in all states and union territories across the country, based on a composite weighted index. The index applies four distinct criteria associated with adolescent girls, including the women's school drop-out rate, girls married before the age of 18, work participation of women, and women literacy rate.[4]

This program is centrally funded by the Government of India, and it covers adolescent girls aged 11-18, including in- and out-of-school girls. It intends to support teenage girls by helping them build the necessary skills for life decision-making, and providing a comprehensive service that focuses on nutrition and health status, reproductive and sexual health education promotion, leading to adolescent girls' enhanced health awareness, self-development and empowerment improvement. The support is offered through several avenues, including providing literacy camps, adult education classes, vocational training as well as creating supporting groups on issues, such as domestic violence and alcoholism, which are of considerable social significance.[5]

The girls gather at the Anganwadis - the important centers that provide primary healthcare services and are recognized as focal places for implementing health and learning initiatives. These centres provide an opportunity for interaction between in- and out-of-school girls that could help motivate out-of-school girls for school attendance, which ultimately helps them acquire life skills and education. The Anganwadi workers (AWW) interview and register eligible adolescent girls within specified Anganwadi centres' jurisdiction. The skilled workers in the centers advise adolescent girls to join the Anganwadi centres at regular inter-

[2] https://wcd.nic.in/sites/default/files/1-SABLAscheme_0.pdf

[3] https://www.indiangovtscheme.com/2021/06/scheme-for-adolescent-girls-sabla.html

[4] https://wcd.nic.in/sites/default/files/1-SablaEVAReportver5.1_0.pdf

[5] https://www.icrw.org/wp-content/uploads/2020/06/What-Works-for-Adolescents-Empowerment-Learning-Review.pdf

vals and receive iron and folic acid supplementation, health check-up and referral services, and nutrition and health education. Other components of the scheme, such as counselling on family welfare and accessing public services, are also mainly facilitated through Anganwadi centres.

Considering the advantages provided under the SABLA program, there are also differences between the beneficiaries' age groups. For instance, under the non-nutrition scheme of SABLA, only out-of-school adolescents of ages 16-18 are provided with vocational training. With regards to the nutritional component of the scheme, although both in-school and out-of-school girls are given take-home rations or hot cooked meals, only in-school girls aged 14-18 years are eligible to receive that. The age criterion is different for the out-of-school adolescents; that is, all girls aged 11-18 are eligible to receive the take-home rations.

3.4 Data

Our data comes from the India Demographic and Health Survey-IV (IDHS-IV) in 2015-16. The DHS, also referred to as the National Family Health Survey (NFHS) in India, is a large nationally representative household survey implemented by the Government of India, and it surveys women aged 15-49, children aged 0-5 years, and men aged 15-54 years. The DHS sample design applies a two-stage probabilistic sampling approach to select clusters (census enumeration units) and households in the first and second stages, respectively. This is the procedure employed in most DHS surveys. The survey comprised 601,509 households and 699,686 eligible women aged 15-49 who completed the interviews. It asks detailed questions about household and individual socioeconomic and health characteristics, including age, educational attainment, number of living children, current work status, wealth index, place of residence, caste, and religion. The DHS is one of India's most extensive demographic and health surveys ever implemented in four rounds, 1992-93, 1998-99, 2005-06, 2015-16. A recently published fact sheet is available for 2019; however, the questions and data have not yet been released.

The central of this paper is women and household questionnaires. In the women's questionnaire, all eligible women aged 15-49 were interviewed for a series of questions concerning their awareness of family planning and reproductive behaviour, participation in decision-making, and knowledge of diarrhoea treatment.[6]

[6] Within each household, women aged 15-49 were surveyed using the women questionnaire, and the unit of analysis is women who were interviewed. In India, only the women who have been married were interviewed. In this case, only ever-married women aged 15-49 are in the IR (women) file.

With regard to the outcome measures, the current paper focuses on representing adolescent girls' assets concerning the health domain and decision-making. Health assets are defined as a) knowledge of family planning (contraceptive) methods and using such methods, and b) diarrhoea treatment knowledge. The decision-making area is categorized into autonomy in relation to a woman's own money, her partner's earnings, and her own health care, alone/jointly with her partner. All defined measures are based on the existing questions in the women's questionnaire of the two applied DHS datasets.

Summary statistics are presented in Tables 3-1 and 3-2, describing our post-program sample's mean and standard errors for considered demographic and socioeconomic controls and outcome measures in the model, respectively, regarding the treated and non-treated groups. Our final data consists of 329,826 "ever-married women" aged 15-28; however, our sample size may vary depending on the specific outcome and number of respondents. The mean age for all women considered in our regression is 21.40 years. Nearly 28% of the respondents define the urban area as their place of residence, and about 73% of the respondents are affiliated with the Hindu religion. The women interviewed reported having completed approximately eight years of schooling. Figure 3-1 shows our identifying variation in treatment (SABLA introduction) across districts. The districts with exposure to the policy are shaded in green.

3.5 Identification strategy

To estimate the impact of the SABLA program on our outcomes, we consider the ITT effect of the SABLA program. In doing so, we count all eligible girls residing in SABLA implemented districts as the treated group, and all those who reside in non-SABLA districts are assigned to the control group, regardless of whether they had participated in the SABLA program. In other words, we consider the program rollout in a district rather than the actual participation of an eligible woman in the program (Gentzkow and Shapiro, 2008). In our main empirical analysis, we employ a difference-in-differences (DID) design that compares our outcome measures between districts with and without SABLA implementation, and across women with and without exposure to SABLA. We estimate the following specification for each given outcome:

$$\begin{aligned} Y_{ihd} = {} & \beta_1(Ever - Exposed_i \times SABLA - District_d) \\ & + \beta_2 Ever - Exposed_i + \beta_3 SABLA - District_d \\ & + \gamma X_i' + \alpha_d + \alpha_a + \alpha_{s,a} + \epsilon_{ihd} \end{aligned} \tag{3.1}$$

where Y_{ihd} denotes the value of each outcome corresponding to woman i in household h, residing in district d. $Ever - Exposed_i$ is an indicator for being in a "treated" cohort (being aged 15–22). This is a dummy variable that takes the value 1 if the given cohort was exposed to the policy and zero otherwise. $SABLA - District_d$ is an indicator that corresponds to the district with SABLA implementation.

β_1 captures the causal effect of potential exposure to SABLA on our outcomes. More precisely, the coefficient gives the intention-to-treat effect of the SABLA program. X_i' is a vector of individual and household level controls that captures any other non-treatment effects, which may potentially make our estimates biased, including education, religion, caste, number of children aged 5 and under in the household, household size, age and sex of the household head, place of residence, and wealth index.

District fixed effects (α_d) and age fixed effects (α_a) in this specification control for any factors affecting our outcomes that are common among eligible women of the same age or residing in the same district (McGavock, 2021). We additionally consider the potential time-invariant determinants of our outcomes that vary by age and state by including fixed effects for state interacted with age ($\alpha_{s,a}$) (Heath and Tan, 2020).

Standard errors are clustered at the district×age level corresponding with the level at which the treatment variable is assigned (Abadie et al., 2017). The interpretation of these results is denominated by the potential exposure to the SABLA program rather than a woman actually being exposed to the program or adopting the program and attending the classes.

Our preferred specification is based on the binary treatment status, exposed vs. non-exposed, as we believe that this type of design provides us with a much simpler measure in understanding the impact of policy exposure on the exposed cohort. In addition, unlike the discussions on formal education in which learning to read and write is clearly dependent on the longer participation in schooling, one is not require to attend a certain amount of sessions in the SABLA program to be beneficial of the discussions; as long as she has had some opportunities to participate, the number of opportunities is not a matter of concern.

Our DID model relies on the parallel trends assumption that in the absence of the SABLA program, the eligible women's outcome would have not been systematically different between districts with and without SABLA implementation. That is, the eligible women residing in the districts with and without SABLA rollout had similar pre-trends in terms of the outcome variables prior to the introduction of the SABLA program. The identification assumption could be violated if the SABLA rollout was related to the districts' pre-treatment demographic and socioeconomic characteristics. We argue in what follows that pre-treatment factors do not drive our findings (See Table 3-13).

Figures 3-3(a)–3-3(f) present a visual demonstration of the baseline characteristics. Since we lack information on our outcome measures and control variables at the district level for the prior survey, the IDHS-III (2005-06), we need to use data from the IDHS-II (1998-99).[7] Therefore, we practically do not test for the parallel trend, yet, test for the level of outcome. We do not observe any systematic difference between the levels of outcomes of interest in the SABLA (treated) and non-SABLA (control) districts in the pre-treatment period.

3.6 Main results

This section presents the impacts of the SABLA program on the three main sets of outcomes targeted by the program: family planning, decision making, and knowledge of infectious disease treatment. For each outcome, we show ITT estimates resulting from our preferred specification in Equation (3.1).

Table 3-3 reports the main results of potential exposure to the SABLA program on family planning measures, decision-making domains, and knowledge of diarrhoea treatment among eligible women. Columns 1 through 3 present the effects concerning family planning module. Our dependant variable comes from the respondents' reports on their knowledge of family planning methods (contraceptive methods), contraception use, and whether the respondents report using modern contraceptive methods.[8]

We find evidence suggesting that women exposed to the SABLA program are more likely to have heard about these methods. More precisely, the likelihood of women knowing contraceptive methods is higher (about 1.0 percentage point) among those who have been potentially exposed to the program than those not exposed. Similarly, the estimate suggests that exposure to the program increases the likelihood of using any contraptions by 0.7 percentage points. However, we find no evidence suggestive of a statistically significant effect on using modern family planning methods despite the positive coefficient, plausibly due to fear of the side effects and health concerns linked to such methods.[9]

In columns 4 through 6 of Table 3-3 we show how three dimensions of females' autonomy

[7] For our identification to better perform the SABLA program impacts, using the previous round of DHS for India (DHS-III), the 2004-2005 survey appears to be beneficial. However, due to confidentiality requirements, the districts identifiers for IHDS-III are not publicly available, and thus, they are not considered in our analysis (Stopnitzky, 2017)

[8] Questions 318, 319, and 321 on Pages 15 and 16 on women questionnaire

[9] https://www.who.int/news/item/25-10-2019-high-rates-of-unintended-pregnancies-linked-to-gaps-in-family-planning-services-new-who-study

in household respond in terms of exposure to the program.[10] The dependent variable is a binary that takes the value 1 if the decision is made alone by a woman or jointly with her partner, zero otherwise. We find strong evidence of increased likelihood of women being allowed to have some money set aside for their use as they wish. However, we do not find a significant increase in women's bargaining power in terms of participation in making decisions about using their husband's earnings and their own health care on account of the policy. Yet, the effects may be heterogeneous with respect to the place of residence, religion, educational attainment, and wealth.[11]

Column 7 of Table 3-3 reports the outcome of estimating the effect of policy exposure on diarrhoea treatment. The respondent is defined to have knowledge of diarrhoea treatment if she has ever heard of "oral rehydration therapy or ORS packets" to treat diarrhoea. It can be seen that the coefficient is positive and significant at the 5% level. Women exposed to SABLA are about 0.5 percentage points more likely to have diarrhoea treatment knowledge than those who are non-exposed.

3.7 Heterogeneous effects of program exposure on outcomes

This section investigates whether the effects of policy exposure accrue more to specific groups. In doing so, we study the heterogeneous effects of policy exposure by including interaction terms between exposure to the SABLA variable and women's demographic characteristics, such as place of residence, religion, educational attainments, and head of household. Investigating the heterogeneous effects may have the ability to direct policy interventions, allowing policies to be better targeted toward certain groups. We conduct this exercise for all eligible women.

3.7.1 Place of residence

To investigate the role of place of residence in the SABLA effects in our setting, we re-estimate the preferred specification with an additional regressor interacting exposure to the SABLA program variable with a dummy that takes the value 1 if the respondent resides in a rural area and zero otherwise.

We repeat the exercise separately for the domain of our outcomes, including family plan-

[10] Questions 923, 924, and 927 on Page 75 on women's questionnaire

[11] The impacts will be studied separately in section 3.7.

ning, decision-making and knowledge of disease treatment. The results of this exercise are reported in column 2 in Tables 3-4–3-7.

For two of our outcome measures, the knowledge of family planning (Panel A) and using modern family planning methods (Panel C), the coefficients on the interaction terms are negative and significant, suggesting that residing in rural areas decreases the treatment effects of program exposure. The reduction is more pronounced concerning modern contraceptive use, with the coefficient on the interaction term of -0.062***.

However, for using any contraceptives and knowledge of diarrhoea treatment, the coefficients on the interaction terms (0.005* and 0.012***, respectively) are positive and significant, suggesting that living in rural areas improves the effect of program exposure.

With regard to other outcomes, namely participation in decision making in the household, residing in rural areas does not appear to have a significant effect when discussing the program exposure.

3.7.2 Educational attainment

To probe the possible differential effects of educational level, similar to the above section, we add a regress to our preferred specification that interacts the SABLA exposure variable with a dummy that takes the value 1 if a respondent falls into a no or primary education category, zero otherwise.

Column 3 in Tables 3-4–3-7, reports the results of this exercise. The coefficients on the interaction term for knowledge of family planning (contraceptive methods), use of any contraception, and knowledge of diarrhoea treatment are negative and significant at the 1% level (-.0.041***, -0.021***, and -0.033***, respectively). Having no or primary level of education decreases the treatment effect on these specific outcome measures significantly. Regarding the rest of our outcomes, including women's autonomy in decision-making, as can be seen, different level of education does not result in significant treatment effect.

Although the SABLA program targeted both in- and out-of-school girls, elaborating on program exposure suggests that having a higher level of education appears to be impactful in acquiring health knowledge. The findings regarding family planning are consistent with the previous literature that established the link between education and lack of knowledge (Andalón et al., 2014; Le and Nguyen, 2020; Skirbekk, 2008).

3.7.3 Religion

To study the role that religious affiliation could play concerning the SABLA effects in our setting, we re-estimate the preferred specification adding a regressor interacting exposure to the SABLA program variable with a dummy that takes the value 1 if the respondent belongs to a Hindu affiliation and zero otherwise. We also run this exercise for the Muslim respondents as Islam is the second most populated religion (14.2% in the 2011 census) in India.

We repeat the exercise separately for the domain of our outcomes. Results are reported in columns 4 and 5 in Tables 3-4–3-7. The coefficient on the Hindu interaction term, -0.027***, suggests a statistically significant decline in using family planning methods. Similarly, the negative and significant coefficient on the interaction term in column 4, -0.113**, points to a statistically significant reduction in the treatment effect for women's autonomy over their earnings. Being a Hindu respondent is not significantly sensitive to the treatment for the rest of our outcomes. Our estimated coefficients for most interaction terms considering the Muslim religion are positive but not statistically significant at the conventional levels. However, in using any contraception, being Muslim significantly increases the program exposure effect (coefficient of 0.016***).

3.7.4 Head of household

To probe the effects of the program through the head of the household, we add a regressor to our preferred specification that interacts the SABLA exposure dummy variable with a dummy that takes the value 1 if a respondent lives in a male-headed household, zero otherwise. We repeat this exercise separately for the range of our outcomes. Our results are presented in columns 6 in Tables 3-4–3-7. We find no evidence that living in a male-headed household decreases the treatment effect except for using any contraception. The coefficient on the interaction term, -0.027***, points to a significant decline in the likelihood of women's bargaining power in the fertility area when living in a male-headed household.

3.7.5 Level of wealth

It is believed that poverty fuels poor health and socioeconomic conditions. To study this in our setting, we add a regressor to our preferred design that interacts the exposure to SABLA variable with a dummy that takes the value 1 if the respondent falls into the category with the above-average wealth, zero otherwise.

The results presented in Tables 3-4–3-7 reveal that except for using any contraception that suggests being wealthier decreases the treatment effect significantly, the positive and statistically significant interaction coefficients for knowledge of family planning, use of modern family planning/ contraceptive methods, and women's participation in how to use their partner's earning points to the sensitivity of the treatment effect in terms of wealth. For instance, the positive and significant coefficient on the interaction term for using modern contraception (0.065***) points again to higher wealth level being an important factor in using modern methods. For the rest of our outcomes, belonging to a category with above-average wealth does not significantly affect the policy impacts.

3.8 Robustness

3.8.1 Alternative specification: Years of exposure to the program

In this section, we explore the robustness of our analysis to the application of an alternative specification. We re-estimate the preferred specification considering the intensive design. We take advantage of the fact that rollout of the SABLA program created exogenous variation in the duration of potential exposure to the program, meaning that some girls would have been exposed to the SABLA program for four/five years, some girls were exposed for three years, and yet others, who were 18 years old and above in 2011, were not eligible for the program. The proposed alternative specification is as follows:

$$\begin{aligned} Y_{ihd} = {} & \beta_1(\mathit{Years} - \mathit{Exposed}_i \times \mathit{SABLA} - \mathit{District}_d) \\ & + \beta_2 \mathit{Years} - \mathit{Exposed}_i + \beta_3 \mathit{SABLA} - \mathit{District}_d \\ & + \gamma X_i' + \alpha_d + \alpha_a + \alpha_{s,a} + \epsilon_{ihd} \end{aligned} \tag{3.2}$$

where $\mathit{Years} - \mathit{Exposed}_i$ indicates the number of years that an eligible adolescent girl would have been exposed to the SABLA program; it equals five as the maximum potential years of exposure and zero as the minimum. $\mathit{SABLA} - \mathit{District}_d$ is a dummy variable that takes the value 1 if the district was assigned to the SABLA program. The coefficient on the interaction term of $\mathit{Years} - \mathit{Exposed}_i$ and $\mathit{SABLA} - \mathit{District}_d$ defines the coefficient of interest, β_1, which will be interpretable as the causal effect of an additional year of potential exposure to the program on the set of our outcomes. Other control variables, as well as level of clustering for standard errors, are identical to what was employed in Equation (3.1).

Table 3-8 reports the results taht consider the $Ever - Exposed_i$ dummy variable replaced by $\mathit{Years} - \mathit{Exposed}_i$. The coefficients of family planning knowledge, use of any contraception, and knowledge of diarrhoea treatment point to a statistically significant but fairly small effect of the exposure intensity. One additional year of exposure to the program, for instance, increases the probability of acquiring knowledge about family planning by 0.3 percentage point. In addition, the positive and significant coefficient on personal finance provides evidence of improvement in women's bargaining power within households. One more year of potential exposure to the program resulted in a 3.1 percentage point increase in the likelihood of women's decision-making autonomy in relation to their own money. The results of this exercise are much in line with our preferred estimates with respect to statistical significance at conventional levels but are smaller in value, providing us with some confidence in the study findings.

3.8.2 Controlling for exposure to the media

It might be argued that exposure to other sources of information, such as different types of media, could be correlated with our outcomes. In other words, the estimated effects of exposure to the SABLA program could plausibly capture the effects of other factors. We further test this possibility by adding exposure to the media index (including television, radio, and newspapers) to our main specification. Table 3-9 summarizes the results. Findings suggest that the estimated coefficients are robust to the inclusion of exposure to media as an additional control.

3.8.3 Alternative upper bound of control group

Our central identification defines 28 as being the age upper bound of the unexposed cohort as it helps to define our control groups across districts and retain enough sample observations for our analysis. Even though there is no particular reason for considering age 28 as the upper bound for the control group in our analysis, the possible sensitivity to the age categories may be of concern, as different age groups may react differently. To explore such a possibility, we re-estimate our preferred specification taking into consideration different upper bounds for the age of the control groups.

Table 3-10 presents the results from considering alternative upper bounds. Columns 1 and 3 in each panel define the new upper bounds as 15-25 and 15-31 for our control group. Column 2 shows our original estimates. The findings confirm that our identification strategy does not seem to be sensitive to different upper bounds for the age of the control group.

3.8.4 Alternative standard error

In Table 3-11 we report the results of re-estimating our main specification considering alternative clustering approaches that may be of preference for some readers. Our primary analysis reported standard errors clustered at the district-age level, corresponding with the level at which the treatment variable is assigned (Abadie et al., 2017).

Column 1 in each panel presents our preferred approach, errors clustered at the district-age level. Column 2 shows the results when standard errors are unclustered. We also adopt age, state×age, and state clustering approaches (Column 3, column 4, and column 5, respectively), following Conley (1999), who introduces higher spatial resolution of clustering for robust standard errors. We observe that the results are consistent with findings from our preferred clustering approach, suggesting that the reported outcome measures may vary according to the place of residence (rural-urban) as well as the economic status of the women, yet these are not sensitive to the level of clustering.

3.8.5 Placebos

The placebo test investigates the effect of a treatment on a variable that we know to be unaffected by that treatment or to be irrelevant. If the estimated coefficients appear to be statistically significant, then the validity of the applied specification is of concern (Hartman and Hidalgo, 2018).

The SABLA program was introduced in late 2010 and provided support to the 11-18 years old adolescent girls, and the boys in the same age group were not the targeted beneficiaries of the program. Therefore, we can conduct two different placebo tests to identify the effect of the program considering using (a) the 1998 IDHS survey (prior to policy rollout) for eligible women (falsely-assigned date) and (b) the 2015 IDHS survey for ineligible groups (falsely-assigned data). If we find a statistically significant coefficient, there is an issue of credibility with regard to our research design.

Table 3-12 contains the results of placebo tests using Equation (3.1) in our setting. The estimated coefficients from the regressions are much smaller than our main results from non-placebo estimation, and they are not statistically significant at conventional levels.

3.8.6 Randomization

To ensure against the potential endogenous assignment of districts, we perform a test of the correlates of treatment status to find whether the SABLA assignment to a district was correlated with individual and household level characteristics at the district level.

We report the results from the regression of the treatment dummy on various district-level variables in Table 3-13. Evidence suggests that we are unable to reject the null hypothesis that socioeconomic and demographic characteristics of individuals and households in the districts are uncorrelated with the treatment assignment, providing some confidence against endogenous program placement.

3.9 Conclusion

In this study, we intend to test the hypothesis that the SABLA scheme would positively impact several indicators of women empowerment. We exploit plausibly exogenous variation in the program's rollout across districts and birth cohorts. Using the DHS data coupled with the difference-in-differences approach, we find evidence suggestive of an improvement in some outcome measures.

More precisely, exposure to SABLA leads to an increase in the likelihood of awareness related to family planning, use of contraception, personal financial decision-making, and diarrhoea treatment knowledge. However, evidence suggests a more significant effect size for women with higher educational attainment and those who reside in urban settings. The Hindu respondents were less advantaged in this regard. Our results are robust to alternative specifications.

The placebo tests and our pre-treatment randomization test combined with a visual inspection of the balance on observables in Figures 3-1 and 3-3(a)–3-3(f) provide us with some evidence against the potential endogenous assignment of the program to districts.

Our findings call into question whether such intervention is an appropriate policy tool. Such policy given to the entire population seems ineffective in improving women's empowerment, at least for the components probed in this study. This might require the policy to focus directly on disadvantaged households in terms of education and place of residence.

Figure 3-1: India map including SABLA districts

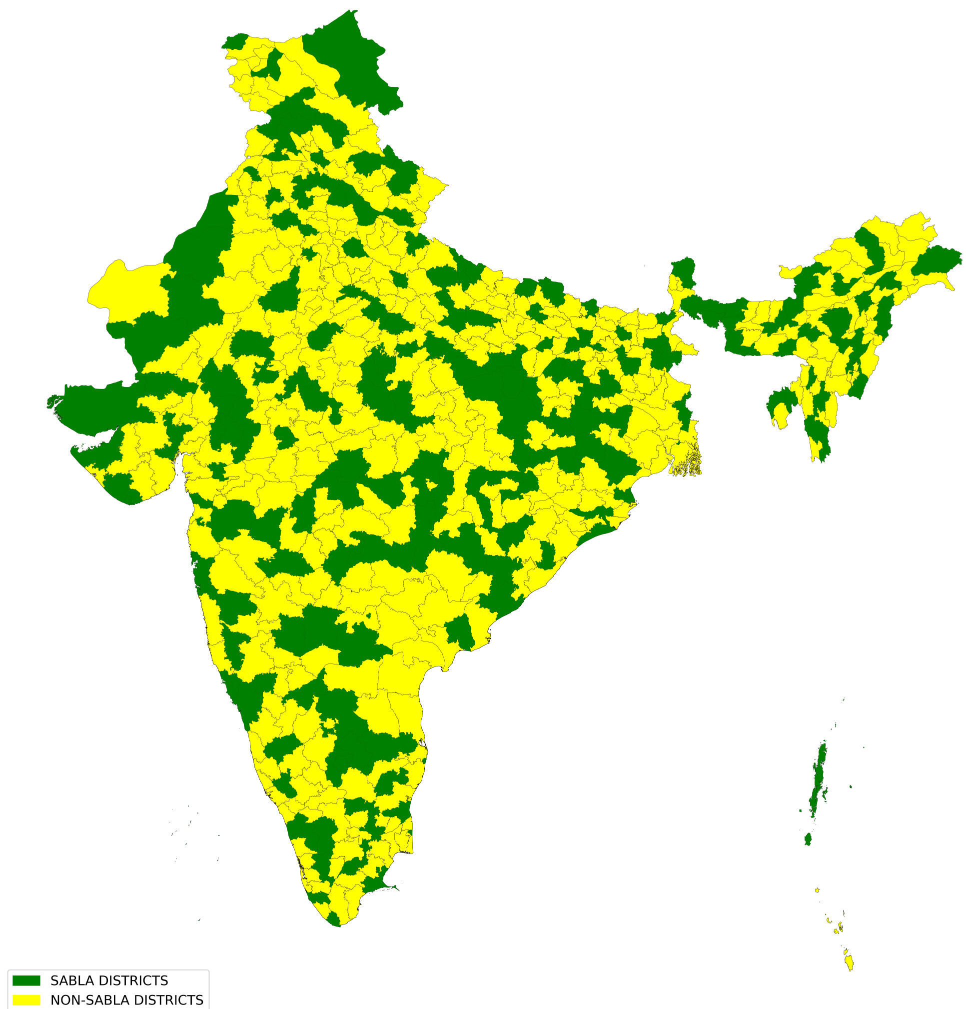
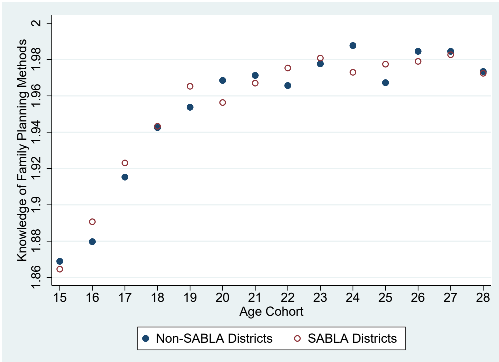
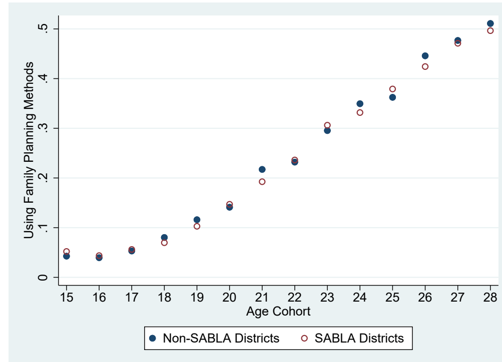


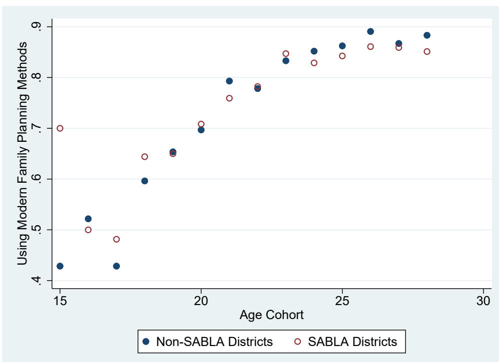
Figure 3-2: Balance on Observable Characteristics 1998–1999



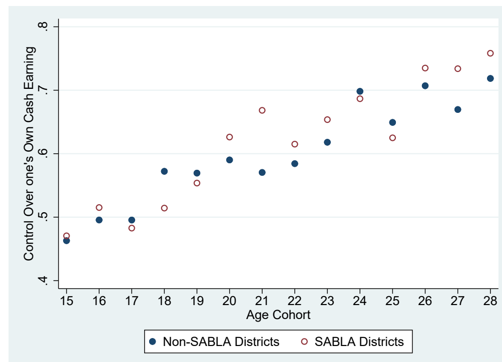
(a) Knowledge of FPM



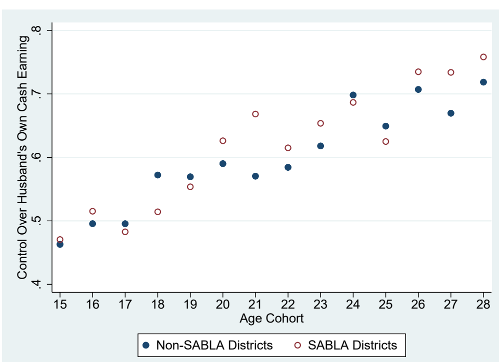
(b) Using FPM



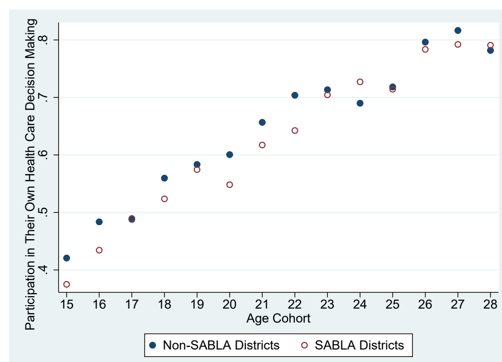
(c) Using Modern FPM (Currently)



(d) Decision Making - Personal Finance



(e) Decision Making - Husband Earning



(f) Decision Making - Personal Health

Table 3-1: Sample means - Control variables

		All	Eligible	Ineligible	Ineligible	Ineligible
Current age	Continuous	21.409	18.246	18.228	25.191	25.169
	Variable	(4.020)	(2.174)	(2.176)	(1.895)	(1.889)
Education in	Continuous	8.395	8.850	8.756	8.129	7.841
Single Years	Variable	(4.602)	(3.802)	(3.842)	(5.325)	(5.342)
Religion	Hindu=1	0.735	0.726	0.733	0.732	0.744
	Other Religion=0	(0.441)	(0.446)	(0.442)	(0.443)	(0.436)
Caste	SC/ST=1	0.384	0.404	0.378	0.397	0.375
	Others=0	(0.486)	(0.491)	(0.485)	(0.489)	(0.484)
Wealth Index	Poorest=1, Poorer=2	2.933	2.919	2.836	3.081	2.989
	Middle=3, Richer= 4	(1.369)	(1.383)	(1.342)	(1.397)	(1.373)
	Richest= 5					
Place of Residence	Urban=1	0.280	0.306	0.256	0.331	0.272
	Rural=0	(0.449)	(0.461)	(0.436)	(0.471)	(0.445)
Household Size	Continuous	6.092	6.086	6.182	5.924	6.064
	Variable	(2.741)	(2.589)	(2.679)	(2.789)	(2.863)
Children below	Continuous	0.756	0.444	0.467	1.079	1.120
5 years in household	Variable	(0.981)	(0.804)	(0.827)	(1.033)	(1.042)
Age of household	Continuous	47.673	48.662	48.761	46.420	46.418
head	Variable	(13.837)	(12.347)	(12.302)	(15.338)	(15.361)
Sex of household	Female=1	0.131	0.136	0.133	0.133	0.127
head	Male=0	(0.338)	(0.343)	(0.339)	(0.339)	(0.333)
Age			15-22	15-22	23-28	23-28
SABLA Age Eligibility			Yes	Yes	No	No
SABLA District			Yes	No	Yes	No

Table 3-2: Sample means : Outcome variables

		All	Eligible	Ineligible	Ineligible	Ineligible
Family Planning						
Knowledge of FP Methods	Knowing no method=0	1.931	1.899	1.894	1.973	1.973
	traditional methods=1	(0.364)	(0.436)	(0.447)	(0 .230)	(0.230)
	modern methods=2					
Using Contraceptive Method	Using no method=0	0.176	0.050	0.053	0.311	0.327
	traditional methods=1	(0.381)	(0.218)	(0.224)	(0.463)	(0.469)
	modern methods=1					
Using Modern Contraceptive Method	Using no method=0	0.144	0.037	.038	0.265	0.274
	traditional methods=0	(0.351)	(0.189)	(0.190)	(0.441)	(0.446)
	modern methods=1					
Decision Making						
Personal Finance	Decide alone or with husband=1	0.775	0.775	0.696	0.806	0.782
	Otherwise=0	(0.417)	(0 .418)	(0.460)	(0.395)	(0.413)
Husband Finance	Decide alone or with husband=1	0.672	0.641	0.627	0.694	0.685
	Otherwise=0	(0.469)	(0.480)	(0.483)	(0.461)	(0.464)
Personal Health	Decide alone=2	1.033	0.985	0.965	1.060	1.053
	Decide with husband/partner=1	(0.433)	(0.475)	(0.465)	(0.416)	(0.416)
	Otherwise=0					
Disease Knowledge						
Diarrhoea-Care Knowledge	Used ORS=1	0.850	0.837	0.824	0.882	0.875
	Heard of ORS=1	(0.356)	(0.369)	(0.381)	(0.322)	(0.331)
	Never heard of=0					
Age			15-22	15-22	23-28	23-28
SABLA Age Eligibility			Yes	Yes	No	No
SABLA District			Yes	No	Yes	No

Table 3-3: Main results

	Effect on Family planning			Effect on Decision Making			Disease Knowledge
	FP Knowledge	Using FP Methods	Using FP Modern Methods	Personal Finance	Husband Finance	Personal Health	Diarrhoea
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ever-Exposed$_i\times$ *SABLA-District*$_d$	0.010***	0.007**	0.007	0.095**	0.009	0.012	0.005**
	(0.003)	(0.003)	(0.010)	(0.038)	(0.013)	(0.015)	(0.002)
R^2	0.09	0.26	0.17	0.27	0.10	0.11	0.14
No. of Observations	329,826	329,826	57,753	4,567	28,063	23,350	329,826

Notes: All columns report estimates for 'ever-married women' model specified in Equation (3.1). The point estimate for the coefficient of interest represents the impact of exposure to SABLA on outcomes of interest. Individual and household controls are religion, caste, education, wealth, sex and age of household head, household size, number of children aged 5 and under in the household, and place of residence (rural or urban). All regressions include district fixed effects, age fixed effects, and state by age fixed effects. Robust standard errors in parentheses and clustered at district × age. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-4: Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PANEL A: Family planning knowledge						
	Preferred	Residence	Education	Hindu	Muslim	Sex of HH Head	Wealth
Ever-Exposed$_i$× SABLA-District$_d$	0.010***	0.018***	0.013***	0.009*	0.012***	0.013**	0.005
	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)	(0.006)	(0.004)
Ever-Exposed$_i$× SABLA-District$_d$ × Rural	-	-0.011^{*}	-	-	-	-	-
	-	(0.004)	-	-	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × No/Low Education	-	-	-0.041^{***}	-	-	-	-
	-	-	(0.009)	-	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Hindu	-	-	-	0.002	-	-	-
	-	-	-	(0.006)	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Muslim	-	-	-	-	-0.011	-	-
	-	-	-	-	(0.007)	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Male Head	-	-	-	-	-	-0.003	-
	-	-	-	-	-	(0.006)	-
Ever-Exposed$_i$× SABLA-District$_d$ × Wealth (≥ average)	-	-	-	-	-	-	0.015***
	-	-	-	-	-	-	(0.004)
No. of Observations	329,826	329,826	329,8266	329,826	329,826	329,826	329,826
	PANEL B: Using Family planning Methods						
	Preferred	Residence	Education	Hindu	Muslim	Sex of HH Head	Wealth
Ever-Exposed$_i$× SABLA-District$_d$	0.007**	0.011***	0.010***	0.028***	0.005	0.031***	0.011***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Ever-Exposed$_i$× SABLA-District$_d$ × Rural	-	0.005*	-	-	-	-	-
	-	(0.003)	-	-	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × No/Low Education	-	-	-0.021^{***}	-	-	-	-
	-	-	(0.004)	-	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Hindu	-	-	-	-0.027^{***}	-	-	-
	-	-	-	(0.003)	-	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Muslim	-	-	-	-	0.016***	-	-
	-	-	-	-	(0.004)	-	-
Ever-Exposed$_i$× SABLA-District$_d$ × Male Head	-	-	-	-	-	-0.027^{***}	-
	-	-	-	-	-	(0.003)	-
Ever-Exposed$_i$× SABLA-District$_d$ × Wealth (≥ average)	-	-	-	-	-	-	-0.010^{***}
	-	-	-	-	-	-	(0.003)
No. of Observations	329,826	329,826	329,8266	329,826	329,826	329,826	329,826
Individual controls	Y	Y	Y	Y	Y	Y	Y
Household controls	Y	Y	Y	Y	Y	Y	Y
District FEs	Y	Y	Y	Y	Y	Y	Y
Age FEs	Y	Y	Y	Y	Y	Y	Y
State-Age FEs	Y	Y	Y	Y	Y	Y	Y
Interaction terms	N	Rural	No/Low Education	Hindu	Muslim	Male HH Head	Wealth (≥ average)

Notes: Dependent variables are knowledge of, and using family planning methods. Column 1 in each panel presents our preferred specification. See notes to Table 3-3 for full list of controls. In each column, interaction terms are the specified dummy (which is 1 if respondent characteristics falls into that category, zero otherwise) times DID variable (Women exposed to the SABLA). Standard errors clustered at district × age level, are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-5: Heterogeneity

	PANEL C: Using Modern Family planning Methods						
	(1) Preferred	(2) Residence	(3) Education	(4) Hindu	(5) Muslim	(6) Sex of HH Head	(7) Wealth
Ever-Exposed$_i$× *SABLA-District*$_d$	0.007	0.053***	0.015	0.014	0.006	−0.027	−0.015
	(0.010)	(0.015)	(0.012)	(0.019)	(0.011)	(0.029)	(0.012)
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Rural*	-	−0.062***	-	-	-	-	-
	-	(0.017)	-	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *No/Low Education*	-	-	−0.028	-	-	-	-
	-	-	(0.019)	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Hindu*	-	-	-	−0.007	-	-	-
	-	-	-	(0.021)	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Muslim*	-	-	-	-	0.009	-	-
	-	-	-	-	(0.027)	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Male Head*	-	-	-	-	-	0.038	-
	-	-	-	-	-	(0.030)	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Wealth* ($\geq$ *average)*	-	-	-	-	-	-	0.065***
	-	-	-	-	-	-	(0.017)
No. of Observations	57,753	57,753	57,753	57,753	57,753	57,753	57,753
	PANEL D: Personal Finance						
	Preferred	Residence	Education	Hindu	Muslim	Sex of HH Head	Wealth
Ever-Exposed$_i$× *SABLA-District*$_d$	0.095**	0.032	0.085*	0.193***	0.093**	−0.012	0.105***
	(0.038)	(0.069)	(0.049)	(0.058)	(0.039)	(0.082)	(0.040)
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Rural*	-	0.077	-	-	-	-	-
	-	(0.072)	-	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *No/Low Education*	-	-	0.021	-	-	-	-
	-	-	(0.059)	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Hindu*	-	-	-	−0.113**	-	-	-
	-	-	-	(0.062)	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Muslim*	-	-	-	-	0.055	-	-
	-	-	-	-	(0.107)	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Male Head*	-	-	-	-	-	0.124	-
	-	-	-	-	-	(0.085)	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Wealth* ($\geq$ *average)*	-	-	-	-	-	-	−0.063
	-	-	-	-	-	-	(0.084)
No. of Observations	4,576	4,576	4,576	4,576	4,576	4,576	4,576
Individual controls	Y	Y	Y	Y	Y	Y	Y
Household controls	Y	Y	Y	Y	Y	Y	Y
District FEs	Y	Y	Y	Y	Y	Y	Y
Age FEs	Y	Y	Y	Y	Y	Y	Y
State-Age FEs	Y	Y	Y	Y	Y	Y	Y
Interaction terms	N	Rural	No/Low Education	Hindu	Muslim	Male HH Head	Wealth ($\geq$ average)

Notes: Dependent variables are using modern family planning methods and decision making about personal finance. Column 1 in each panel presents our preferred specification. See notes to Table 3-3 for full list of controls. In each column, interaction terms are the specified dummy (which is 1 if respondent characteristics falls into that category, zero otherwise) times DID variable (Women exposed to the SABLA). Standard errors clustered at district × age level, are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-6: Heterogeneity (continued)

	PANEL E: Husband Finance						
	(1) Preferred	(2) Residence	(3) Education	(4) Hindu	(5) Muslim	(6) Sex of HH Head	(7) Wealth
Ever-Exposed$_i$× *SABLA-District*$_d$	0.009	0.024	0.014	0.025	0.007	0.006	−0.004
	(0.013)	(0.024)	(0.015)	(0.025)	(0.014)	(0.028)	(0.015)
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Rural*	-	−0.018	-	-	-	-	-
	-	(0.025)	-	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *No/Low Education*	-	-	−0.012	-	-	-	-
	-	-	(0.021)	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Hindu*	-	-	-	−0.019	-	-	-
	-	-	-	(0.027)	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Muslim*	-	-	-	-	0.027	-	-
	-	-	-	-	(0.034)	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Male Head*	-	-	-	-	-	0.004	-
	-	-	-	-	-	(0.028)	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Wealth* ($\geq$ *average)*	-	-	-	-	-	-	0.049**
	-	-	-	-	-	-	(0.024)
No. of Observations	28,063	28,063	28,063	28,063	28,063	28,063	28,063
	PANEL F: Personal Health						
	Preferred	Residence	Education	Hindu	Muslim	Sex of HH Head	Wealth
Ever-Exposed$_i$× *SABLA-District*$_d$	0.012	0.030	0.022	0.031	0.010	−0.019	0.004
	(0.015)	(0.028)	(0.016)	(0.024)	(0.015)	(0.035)	(0.016)
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Rural*	-	−0.023	-	-	-	-	-
	-	(0.030)	-	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *No/Low Education*	-	-	−0.032	-	-	-	-
	-	-	(0.025)	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Hindu*	-	-	-	−0.023	-	-	-
	-	-	-	(0.026)	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Muslim*	-	-	-	-	0.016	-	-
	-	-	-	-	(0.034)	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Male Head*	-	-	-	-	-	0.036	-
	-	-	-	-	-	(0.036)	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Wealth* ($\geq$ *average)*	-	-	-	-	-	-	0.026
	-	-	-	-	-	-	(0.027)
No. of Observations	22,350	22,350	22,350	22,350	22,350	22,350	22,350
Individual controls	Y	Y	Y	Y	Y	Y	Y
Household controls	Y	Y	Y	Y	Y	Y	Y
District FEs	Y	Y	Y	Y	Y	Y	Y
Age FEs	Y	Y	Y	Y	Y	Y	Y
State-Age FEs	Y	Y	Y	Y	Y	Y	Y
Interaction terms	N	Rural	No/Low Education	Hindu	Muslim	Male HH Head	Wealth ($\geq$ average)

Notes: Dependent variables are autonomy on husband's earnings and her personal health care . Column 1 in each panel presents our preferred specification. See notes to Table 3-3 for full list of controls. In each column, interaction terms are the specified dummy (which is 1 if respondent characteristics falls into that category, zero otherwise) times DID variable (Women exposed to the SABLA). Standard errors clustered at district × age level, are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-7: Heterogeneity (continued)

	PANEL G: DIARRHOEA						
	(1) Preferred	(2) Residence	(3) Education	(4) Hindu	(5) Muslim	(6) Sex of HH Head	(7) Wealth
Ever-Exposed$_i$× *SABLA-District*$_d$	0.005**	0.013***	0.010***	0.003	0.005*	0.010**	0.006**
	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.005)	(0.003)
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Rural*	-	0.012***	-	-	-	-	-
	-	(0.004)	-	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *No/Low Education*	-	-	−0.033***	-	-	-	-
	-	-	(0.006)	-	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Hindu*	-	-	-	0.002	-	-	-
	-	-	-	(0.004)	-	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Muslim*	-	-	-	-	0.005	-	-
	-	-	-	-	(0.005)	-	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Male Head*	-	-	-	-	-	−0.006	-
	-	-	-	-	-	(0.005)	-
Ever-Exposed$_i$× *SABLA-District*$_d$ × *Wealth (≥ average)*	-	-	-	-	-	-	−0.004
	-	-	-	-	-	-	(0.004)
R^2	0.14	0.14	0.14	0.14	0.14	0.14	0.14
No. of Observations	329,826	329,826	329,8266	329,826	329,826	329,826	329,826
Individual controls	Y	Y	Y	Y	Y	Y	Y
Household controls	Y	Y	Y	Y	Y	Y	Y
District FEs	Y	Y	Y	Y	Y	Y	Y
Age FEs	Y	Y	Y	Y	Y	Y	Y
State-Age FEs	Y	Y	Y	Y	Y	Y	Y
Interaction terms	N	Rural	No/Low Education	Hindu	Muslim	Male HH Head	Wealth (≥ average)

Notes: Dependent variable is diarrhoea care knowledge. Column 1 in Panel G presents our preferred specification. See notes to Table 3-3 for full list of controls. In each column, interaction terms are the specified dummy (which is 1 if respondent characteristics falls into that category, zero otherwise) times DID variable (Women exposed to the SABLA). Standard errors clustered at district × age level, are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-8: Alternative specification - Years of exposure specification

	Effect on Family planning			Effect on Decision Making			Disease Knowledge
	FP Knowledge	Using FP Methods	Using FP Modern Methods	Personal Finance	Husband Finance	Personal Health	Diarrhoea
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Years-Exposed$_i\times$ *SABLA-District*$_d$	0.003***	0.002**	0.001	0.031**	0.003	0.001	0.002**
	(0.001)	(0.001)	(0.004)	(0.014)	(0.005)	(0.005)	(0.001)
R^2	0.09	0.26	0.17	0.27	0.10	0.11	0.14
No. of Observations	329,826	329,826	57,753	4,576	28,144	22,350	329,826

Notes: Notes: All columns report estimates for 'ever-married women' model specified in Equation (3.2). The point estimate for the coefficient of interest represents the impact of exposure to SABLA on outcomes of interest. Individual and household controls are religion, caste, education, wealth, sex and age of household head, household size, number of children aged 5 and under in the household, and place of residence (rural or urban). All regressions include district fixed effects, age fixed effects, and state by age fixed effects. Robust standard errors in parentheses and clustered at district × age. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-9: Robustness - Exposure to media

	Effect on Family planning			Effect on Decision Making			Disease Knowledge
	FP Knowledge	Using FP Methods	Using FP Modern Methods	Personal Finance	Husband Finance	Personal Health	Diarrhoea
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Ever\text{-}Exposed_i \times SABLA\text{-}District_d$	0.010***	0.007**	0.008	0.095**	0.009	0.012	0.005**
	(0.003)	(0.003)	(0.010)	(0.038)	(0.013)	(0.015)	(0.002)
Exposure to Media Index	0.008***	0.001***	0.007***	0.001	0.012***	0.003	0.012***
	(0.0004)	(0.0003)	(0.001)	(0.004)	(0.002)	(0.002)	(0.000)
R^2	0.09	0.26	0.17	0.28	0.10	0.11	0.14
No. of Observations	329,826	329,826	57,753	4,576	28,144	22,350	329,826

Notes: Notes: All columns report estimates for 'ever-married women' model specified in Equation (3.1). The point estimate for the coefficient of interest represents the impact of exposure to SABLA on outcomes of interest. Individual and household controls are religion, caste, education, wealth, sex and age of household head, household size, number of children aged 5 and under in the household, and place of residence (rural or urban). All regressions include district fixed effects, age fixed effects, and state by age fixed effects. Robust standard errors in parentheses and clustered at district × age. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-10: Main results - Different upper bounds for control group

	PANEL A: FP KNOWLEDGE			PANEL B: USING FP METHODS		
	(1) (15-25)	(2) (15-28) Base	(3) (15-31)	(1) (15-25)	(2) (15-28) Base	(3) (15-31)
Ever-Exposed$_i \times$ *SABLA-District*$_d$	0.013***	0.010***	0.011***	0.009***	0.007**	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R^2	0.09	0.09	0.09	0.22	0.26	0.29
No. of Observations	264,938	329,826	388,781	264,938	329,826	388,781
	PANEL C: USING MODERN FPM			PANEL D: PERSONAL FINANCE		
	(15-25)	(15-28) Base	(15-31)	(15-25)	(15-28) Base	(15-31)
Ever-Exposed$_i \times$ *SABLA-District*$_d$	0.013	0.007	0.006	0.083*	0.095**	0.083**
	(0.011)	(0.010)	(0.010)	(0.048)	(0.038)	(0.036)
R^2	0.18	0.17	0.17	0.36	0.27	0.22
No. of Observations	30,672	57,753	88,113	2,597	4,576	6,868
	PANEL E: HUSBAND FINANCE			PANEL F: PERSONAL HEALTH		
	(15-25)	(15-28) Base	(15-31)	(15-25)	(15-28) Base	(15-31)
Ever-Exposed$_i \times$ SABLA–District$_d$	0.001	0.009	0.015	0.017	0.012	0.014
	(0.015)	(0.013)	(0.013)	(0.016)	(0.015)	(0.014)
R^2	0.11	0.10	0.09	0.012	0.11	0.10
No. of Observations	18,417	28,063	37,355	14,658	22,350	29,814
	PANEL G: DIARRHOEA KNOWLEDGE					
	(15-25)	(15-28) Base	(15-31)			
Ever-Exposed$_i \times$ *SABLA-District*$_d$	0.004**	0.005**	0.004*			
	(0.003)	(0.002)	(0.002)			
R^2	0.14	0.14	0.14			
No. of Observations	264,938	329,826	388,781			

Notes: All columns report estimates for 'ever-married women' model specified in Equation (3.1). The point estimate for the coefficient of interest represents the impact of exposure to SABLA on outcomes of interest. Individual and household controls are religion, caste, education, wealth, sex and age of household head, household size, number of children aged 5 and under in the household, and place of residence (rural or urban). All regressions include district fixed effects, age fixed effects, and state by age fixed effects. Columns 1 and 3 in each panel present the new upper bounds as 15-25 and 15-31, and column 2 shows our preferred estimates. Robust standard errors in parentheses and clustered at district × age. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-11: Alternative standard errors

PANEL A: Family planning Knowledge

	(1) District & Age Preferred	(2) Unclustered	(3) Age	(4) State & Age	(5) State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.010***	0.010***	0.010***	0.010***	0.010**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
R^2	0.09	0.09	0.09	0.09	0.09
No. of Observations	329,826	329,826	329,826	329,826	329,826

PANEL B: Using Family planning Methods

	(1) District & Age Preferred	(2) Unclustered	(3) Age	(4) State & Age	(5) State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.007**	0.007***	0.007**	0.007**	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
R^2	0.26	0.26	0.26	0.26	0.26
No. of Observations	329,826	329,826	329,826	329,826	329,826

PANEL C: Using Modern Family planning Methods

	District & Age Preferred	Unclustered	Age	State & Age	State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.007	0.007	0.007	0.007	0.007
	(0.010)	(0.010)	(0.009)	(0.010)	(0.012)
R^2	0.17	0.17	0.17	0.17	0.17
No. of Observations	57,753	57,753	57,753	57,753	57,753

PANEL D: Personal Finance

	District & Age Preferred	Unclustered	Age	State & Age	State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.095**	0.095**	0.095***	0.095**	0.095**
	(0.038)	(0.039)	(0.031)	(0.038)	(0.038)
R^2	0.28	0.28	0.28	0.28	0.28
No. of Observations	4,576	4,576	4,576	4,576	4,576

PANEL E: Husband Finance

	District & Age Preferred	Unclustered	Age	State & Age	State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.009	0.010	0.010	0.010	0.010
	(0.013)	(0.014)	(0.015)	(0.013)	(0.010)
R^2	0.10	0.10	0.10	0.10	0.10
No. of Observations	28,063	28,063	28,063	28,063	28,063

PANEL F: Personal Health

	District & Age Preferred	Unclustered	Age	State & Age	State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.012	0.012	0.012	0.012	0.012
	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
R^2	0.11	0.11	0.11	0.11	0.11
No. of Observations	22,350	22,350	22,350	22,350	22,350

PANEL G: Diarrhoea

	District & Age Preferred	Unclustered	Age	State & Age	State
Ever-Exposed$_i$× *SABLA-District*$_d$	0.005**	0.005**	0.005**	0.005**	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
R^2	0.14	0.14	0.14	0.14	0.14
No. of Observations	329,826	329,826	329,826	329,826	329,826

Notes: All columns report estimates for 'ever-married women' model specified in Equation (3.1). See notes to Table 3-3 for full list of controls. Column 1 in each panel presents the results of our preferred specification. Standard errors are unclustered in column 2, clustered at age level in column 3, clustered at state by age in column 4, and at state level at column 5. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-12: Placebo

	Family planning Knowledge			Using Family planning Methods			Personal Finance		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Base	1998 Survey	Men 2015 Survey	Base	1998 Survey	Men 2015 Survey	Base	1998 Survey	Men 2015 Survey
Ever-Exposed$_i \times$ *SABLA-District*$_d$	0.010***	0.005	−0.004	0.007**	0.000	0.000	0.095**	0.035	0.022
	(0.003)	(0.005)	(0.006)	(0.003)	(0.008)	(0.005)	(0.038)	(0.025)	(0.016)
R^2	0.09	0.09	0.09	0.26	0.23	0.11	0.27	0.23	0.12
No. of Observations	329,826	37,627	46,687	329,826	37,627	46,687	4,567	7,129	12,042

Notes: Dependent variables are knowledge of family planning, using family planning methods, and personal finance decision-making. See notes to Table 3-3 for full list of controls. Standard errors clustered at district × age level, are reported in parentheses. Column 1 in each panel presents our preferred specification. Columns 2 and 3 falsely-assigned data from the 1998 women survey and the 2015 men survey. *, ** and *** indicate significance at 10%, 5% and 1%.

Table 3-13: Randomization test

	(1) Age First Married	(2) Age at First Birth	(3) Owns Land (Alone/Jointly)	(4) Owns House (Alone/Jointly)	(5) Currently Working	(6) Household has Electricity	(7) Source of Drinking Water	(8) Household has Telephone	(9) Media Exposure
$Ever\text{-}Exposed_i \times SABLA\text{-}District_d$	−0.032	−0.019	0.004	0.006	−0.003	0.001	−0.001	−0.0001	0.004
	(0.030)	(0.030)	(0.007)	(0.008)	(0.007)	(0.002)	(0.003)	(0.001)	(0.012)
R^2	0.28	0.25	0.14	0.16	0.09	0.29	0.36	0.08	0.49
No. of Observations	175,885	136,096	56,876	56,876	56,876	313,924	329,826	313,924	329,826

Notes: All regressions have the same specification as our preferred model but with different outcome variable in each column. See notes to Table 3-3 for full list of controls. Standard errors clustered at district × age, are reported in parentheses. *, ** and *** indicate significance at 10%, 5% and 1%.

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