# *Effect of Early Life Exposure to the Green Revolution on Aging Outcomes in India*[*]

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**Abstract**

The Green Revolution is one of the most significant shocks to agricultural productivity gains that substantially improved economic outcomes in developing nations. However, its long-term impact on aging-related outcomes is not well understood. We examine how early life exposure to the Green Revolution affects later life physical and cognitive health outcomes using the Longitudinal Aging Study in India (LASI). We find that exposure to the Green Revolution from the in-utero period to age 2 significantly improved later-life cognitive function, especially among socially disadvantaged groups (lower Castes) and people born in rural areas. Specifically, a one standard deviation increase in exposure to the Green Revolution in early life improved later-life cognitive function by 0.058-0.113 standard deviations. Significant improvements in schooling and financial conditions in childhood partially explain positive gains in cognitive health. Using the universe of school data, we rule out the possibility that school construction was driving positive gains in schooling as well as the possibility that improvements in height were driving the benefits in cognitive function. These findings have important modern policy implications, as many developing countries are in the

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early stages of adopting the Green Revolution, but they will face a more significant aging population in the coming years than the global average.

# 1 Introduction

The Green Revolution is arguably the single most significant shock to agricultural productivity gains in developing countries and one of the most significant technological innovations of the 20th century (Gollin *et al.*, 2021). The Green Revolution started with the development of high-yield crop variants (HYV) in the 1960s, which dramatically increased the yield of major crops like wheat and rice.[1] Due to its success, it was adopted worldwide to produce more food for a growing population throughout the developing world.

A significant body of research suggests mixed effects of the Green Revolution. On one hand, the adoption of HYVs improved development indicators such as agricultural yields, food security, and per capita GDP while reducing negative externalities such as food prices, poverty, fertility, and child mortality in developing regions (Foster and Rosenzweig, 1996, Evenson and Gollin, 2003, Goltz *et al.*, 2020, Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021). On the other hand, the Green Revolution increased infant mortality rate due to exposure to the use of agrochemicals (Brainerd and Menon, 2014). Additionally, the Green Revolution has been associated with an increased prevalence of mid-life chronic conditions, primarily due to dietary changes during gestation and infancy (Sekhri and Shastry, 2024). One may expect persistent positive effects of early life exposure to the Green Revolution on later life outcomes due to more availability of food and nutrition coupled with higher family income.[2] Conversely, exposure to excess agrochemicals and adverse changes in dietary habits can potentially have detrimental effects on later life outcomes. So, the net long-term effect is ambiguous. Research, however, has not yet explored whether early-life exposure to this massive shock impacted later-life aging-related outcomes.

This paper evaluates whether early-life exposure to the Green Revolution affected long-term aging outcomes in India. We use district panel data on HYV crops to measure exposure to the Green Revolution. Our primary treatment is the share of the area planted under

[1] Norman Borlaug, who led the initiative to develop high-yield crops, received a Nobel Prize in 1970. Various reports referred to Borlaug as "The Man Who Saved a Billion Lives" (MacAray, 2015).

[2] This hypothesis is based on the growing literature that documents the link between early childhood conditions and long-term outcomes, which is mainly focused on the developed countries (Barker, 1990, Almond, 2006, Currie and Almond, 2011, Hoynes *et al.*, 2016, Aizer *et al.*, 2016, Duque and Schmitz, 2023).

the HYV crops in a district in a given year. To measure the aging outcomes, we use the Longitudinal Aging Study in India (LASI), the world's largest and India's first national health and retirement study of individuals aged 45+ collected during 2017-18 (Bloom *et al.*, 2021). The LASI includes comprehensive measures of the health, social, and economic aspects of older adults in India. A key feature of this dataset is that respondents were asked about their birth district, which enhances the precision in measuring early life exposure to the Green Revolution. We match LASI data with the HYV crop data using the respondents' birth district and birth year. We focus on the cohort born between 1966 and 1974 because the Green Revolution began in India in 1966, and the youngest representative cohort in the LASI survey was born in 1974, with the sample respondents between the ages of 45 and 54. Our key outcome variable to measure physical health is the total number of chronic conditions, and to measure cognitive health, we use the general cognition score. In the empirical specification, we exploit the temporal and spatial variation in the HYV crops across districts over time. Further, we explore the heterogeneous treatment effects based on gender, caste, and region, given the stronger gender, caste, and regional norms in India. Finally, we explore both demand-side and supply-side potential mechanisms through which early life exposure to the Green Revolution may affect later life outcomes. Specifically, we explore the role of early-life nutritional investment, financial condition, education, and school construction.

We find marginally significant evidence that early-life exposure to the Green Revolution positively affected later-life cognitive function. Specifically, a one SD exposure to the HYVs in early life (in-utero to age two) leads to a 0.058 SD increase in cognitive function among the 45-54 age group, statistically significant at 10% level.[3] Importantly, our results indicate stronger effects for individuals from lower caste and individuals born in rural areas, with the strongest effect for low caste individuals born in rural areas. Specifically, estimates for these subgroups show improved later-life cognitive function between 0.083 and 0.123 standard deviations and are statistically significant. These effects are comparable and, in some cases, exceed those of other key life factors associated with later-life cognition, including height (0.05), extra grade in school (0.04-0.08), and a positive weather shock (0.06). Conversely, we also document the adverse effect of the Green Revolution in an increase in chronic conditions among men and individuals born in urban areas, providing evidence for the 'double burden

[3]These effects can (loosely) be comparable with a recent study which finds a one SD improvement in weather conditions during age two leads to an improvement in cognition during adulthood (aged 16-37) by 0.063 SDs in a comparable developing country (Webb, 2024).

of malnutrition,' which suggests that the high rate of undernutrition and growing chronic conditions due to overconsumption exist at the same time.[4]

To explore the potential channels for positive gains in the general cognitive score, we show that early life exposure to the Green Revolution significantly improved schooling and financial conditions in childhood, especially among the lower caste individuals and individuals born in rural areas. Further, using the universe of the schooling data, we rule out that the school construction was increasing, and that might have improved gains in schooling and eventually in cognition. Finally, we also rule out that improvement in height, which is one of the key measures of nutrition and human capital development, is driving the benefits in cognitive function.[5] These findings imply that the positive effect of HYVs on later-life cognitive function was primarily mediated through education and income channels, especially for lower-caste and rural areas.[6]

This paper makes several contributions to the economics literature. First, we contribute to the literature by providing one of the first evidence focusing on long-term outcomes for the population from low- and middle-income countries (LMIC) using the largest aging data.[7] Very little is known about the early-life investments and later-life aging-related outcomes in developing countries, where accelerated aging and limited clinical care have led to poorly understood aging and ADRD risk trajectories (NIA Report, 2019). Aging looks different in LMICs from the US, with multi-generational living arrangments offer support to older adults. However, unlike in the US, depression in LMICs increases with age, likely due to limited healthcare access, inadequate pensions, and fewer retirement opportunities (Banerjee *et al.*, 2023). There is a small and growing literature on aging from the LMICs, however, most of which is descriptive, associative, limited in the sample size or scope, and focused on other non-health outcomes (Dias *et al.*, 2008, Srivastava *et al.*, 2021, Huangfu and Nobles, 2022, Banerjee *et al.*, 2023, Alzua *et al.*, 2023).[8] One of the primary reasons for the lack of evidence from developing countries is that detailed aging data was not available until

[4]These effects are consistent with a recent study which finds that the Green Revolution increases the likelihood of diabetes among men in India (Sekhri and Shastry, 2024).

[5]These effects also echo the literature that does not find the early life exposure to a shock on the height (Bharadwaj *et al.*, 2020, Webb, 2024).

[6]This evidence is consistent with the literature that suggests a higher reduction in child mortality for low-caste mothers and children born in rural areas (Bharadwaj *et al.*, 2020).

[7]Only 17 out of 528 studies referred by Global Burden of Disease were designed to study the older population from the LMICs (Banerjee *et al.*, 2023).

[8]There is also a small literature focusing on old-age pension from the LMICs (Bando *et al.*, 2020, 2022).

recently. We use the newly available LASI data from India, which is considered the largest aging data in the world, with over 65,000 respondents in the 45+ age group, which includes detailed health, economic, and social well-being of India's elderly population, to answer the empirical question we study.

Secondly, to our knowledge, this is the first study to explore the linkages between the Green Revolution and long-term cognitive health and one of the first studies to explore the novel potential mechanisms at the individual level, with substantial evidence on the low castes individuals and rural areas. Cognitive health outcomes are a relatively newer area of research in the economics literature.[9] Research on the Green Revolution focus on several other aspects of health and suggests mixed evidence. For instance, research indicates that the Green Revolution has resulted in both an increase and a decrease in child mortality, as well as an increase in metabolic syndrome (Brainerd and Menon, 2014, Sekhri and Shastry, 2024, Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021).[10] We contribute by providing empirical evidence on whether the short-term benefits and costs of the Green Revolution translate to the two key long-term aspects of aging, i.e., the number of chronic conditions and cognitive health. Most evidence on the impact of the Green Revolution on key mechanisms like education is at the aggregate level, focusing on relatively short-term effects and including small-scale studies (Foster and Rosenzweig, 1996). We contribute by exploring novel mechanisms at the individual level, such as educational attainment, childhood financial condition, and height, as a proxy for early-life nutritional investment. We also use the universe of schooling data to evaluate whether the impact of the Green Revolution translates through school construction. Importantly, our strongest effects of cognitive gains are among lower-caste individuals, which underscore the Green Revolution's significant role in mitigating some of the negative externalities of historical caste discrimination, which restricted access to societal resources such as health, water, education, and electricity for lower caste groups.[11]

Third, we contribute to the literature on fetal origins by exploring the extent to which exposure to agriculture investment in the first years of life influences later life health and

[9] Notable studies on cognitive function, primarily from the LMICs include (Barker *et al.*, 2022, McKelway *et al.*, 2022).

[10] We could find only one study that explores the impact of the Green Revolution over a few decades of exposure focusing on the chronic condition (Sekhri and Shastry, 2024).

[11] Studies document such caste-based discrimination in India (Banerjee and Somanathan, 2007, Desai and Kulkarni, 2008, Kaletski and Prakash, 2016).

identifying the critical period of development. Fetal origins research is a relatively newer area in the economics literature and has shown that changes in nutrition, stress, income, and the disease environment during pregnancy increase the risk for Type II diabetes, hypertension, coronary and artery disease (Almond, 2006, Hoynes *et al.*, 2016, Aizer *et al.*, 2016). Research suggests the importance of the prenatal and early childhood years in setting the foundations for life-long success (Barker, 1990, Currie and Almond, 2011). However, there exists very little causal work on how much the timing of the shocks matters for later life cognitive development, and research highlighting the critical period of development from the LMICs is virtually absent.[12] A few studies document the shocks across ages, and usually, in-utero to age 5 is considered a critical period for later life outcomes (Hoynes *et al.*, 2016, Almond *et al.*, 2018, Webb, 2024, Duque and Schmitz, 2023). This paper fills the gap in the literature by studying the impacts of one of the largest agricultural shocks in the world's history on later-life aging-related outcomes and specifying the critical period of cognitive development.

Finally, we improve on existing literature by precisely identifying individuals' birth districts, allowing for a more accurate estimation of their exposure to the Green Revolution. This dimension has been largely overlooked in observational studies from developing nations, including studies focused on the Green Revolution, due to the lack of birth location data. In the absence of precise birth locations, other studies relied on assumptions of no or little migration, i.e., the individuals did not move from their birth districts to their current districts.[13] We, however, do not have to make such an assumption which helps us to minimize measurement errors and maximize the precision.

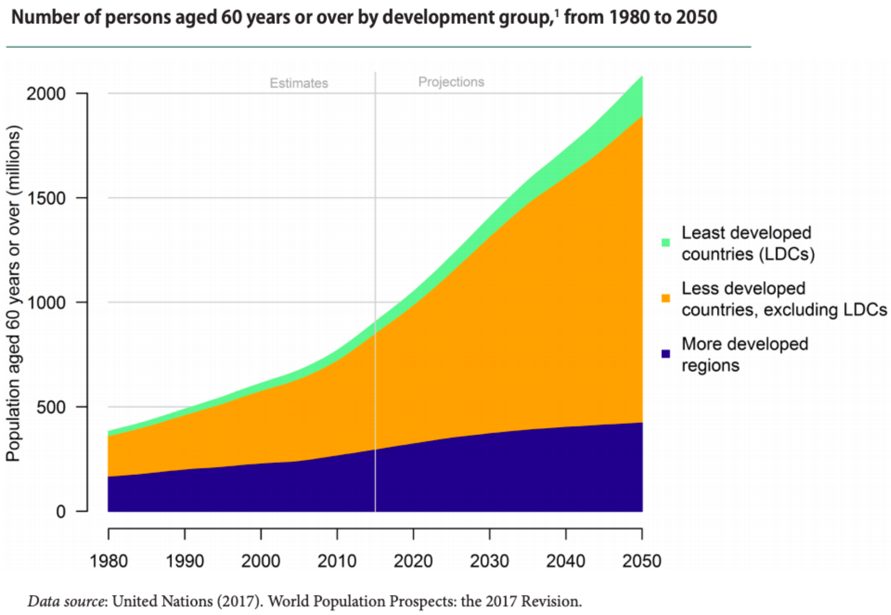
There are at least four reasons to study the effects of the Green Revolution on long-term aging-related outcomes that have important modern policy implications in the developing world. First, the aging population is growing in the world and is (and will be) much higher in developing countries (Figure 1). By 2050, one in five people in poor nations will be over 60 years old. Falling fertility rates and increased life expectancy from improvements in health care, especially in Asia, have led to a rapidly aging population and, with it, a higher prevalence of age-related health problems.[14] Similarly, a major share of the people with

[12] We found only one study that focuses on the critical period of development from the LMICs (Webb, 2024).

[13] Notable studies include Sekhri and Shastry (2024), Webb (2024).

[14] For example, a rapid increase in older populations is projected to also rise in ADRD, from about 47 million people worldwide in 2015 to more than 152 million in 2050, with over three-quarters of the people with ADRD from low- and middle-income countries.[15]

FIGURE 1: Share of older people across the world




Source: United Nations Report, 2017

Alzheimer's Disease and Related Dementias (ADRD) live in low and middle-income countries. However, much of the evidence from the fetal origins literature focuses on high-income countries, yet there is an urgent need to understand how the long reach of childhood shocks affects long-term wellbeing in developing nations, given diverse cultural and demographic factors.[16] Secondly, the relationship between early life shocks and later life health could be complex in LMICs since individuals are subject to repeated shocks throughout their childhood. This is particularly essential to understand the critical period of early life for the development of later life outcomes. Furthermore, investigating the underlying relationships in the contexts of developing countries was challenging primarily due to the lack of detailed long-term empirical data until recently. Finally, the Green Revolution is an ongoing policy yet to be adopted in several parts of developing countries, including Sub-Saharan Africa.[17] From a policy perspective, it's crucial to understand if the short-term benefits and costs of

[16] Indeed, National Institute of Aging (NIA) has emphasized the urgent need to study aging and ADRD risk in developing countries because well-known patterns of aging documented in high-income countries (HICs) may not be generalizable in LMICs, where contexts differ dramatically from those experienced in HICs (NIA Report (2019)).

[17] For instance, Sub-Saharan African countries started investing in these technologies in much later decades compared to Asia and Latin America, primarily due to differences in the type of the crop consumption. While rice and wheat were prominent in Asia and Latin America, the advancements in Maize (a dominant staple in African countries) started after several decades (Carter *et al.*, 2021).

the Green Revolution continue in the long term. In the context of India, another important reason is that currently 70% of rural households in India ($\sim$ 630 million people) still depend on agriculture for their livelihood.[18]

Our analysis may suffer from limitations due to non-random adoption of HYVs, and we address them in various ways.[19] As documented in Bharadwaj *et al.* (2020), the different prevalence of the adoption of the Green Revolution in different regions was primarily dependent on various input factors. For instance, northern states adopted the HYVs earlier due to the canal irrigation network developed during the colonial era. We addressed these challenges in the following ways. First, to address the temporal and spatial factors associated with the adoption of the HYV, which might also affect health later in life, we include the birth district and birth year fixed effects. Additionally, we also include birth state-specific linear time trends or birth state-by-year fixed effects.[20] Similarly, we control for the various characteristics at the individual level like parental education, gender, castes, regional characteristics like rainfall, and temperature, and other district-level characteristics from the Census like literacy rate, gender ratio, and share of rural population. Finally, we also show tests for the robustness checks that strengthen our confidence in estimates.

# 2 Background

In the second half of the twentieth century, after the end of colonial regimes, the economic development policies were growing. Global concerns regarding low levels of agricultural productivity and the increasing issue of food insecurity prompted donor agencies to allocate resources towards agricultural research.[21] The investments made in the early 1960s were the cornerstone for the successes at the International Maize and Wheat Improvement Centre (CIMMYT) in Mexico and the International Rice Research Institute (IRRI) in the Philippines and can be credited to the inception of the Green Revolution (Pingali, 2012, Gollin

[18] Refer summary provided by The Food and Agricultural Organization of the United Nations (FAO).

[19] Our empirical specification is closer to Bharadwaj *et al.* (2020) and Webb (2024). Bharadwaj *et al.* (2020) examine the effect of the Green Revolution on child mortality in India, while Webb (2024) studies the effect of weather shock on cognitive development in Indonesia.

[20] The first takes into account any unobserved trending variables that may vary by state-specific cohorts, and the second accounts for any annual pattern in later life outcomes that may differ across states.

[21] The donor agencies include the Ford Foundation and the Rockefeller Foundation.

*et al.*, 2021).[22] The success of this development of high-yielding crop varieties (HYV) is typically referred to as a "Green Revolution" (Evenson and Gollin, 2003).[23] Further, the Consultative Group on International Agricultural Research (CGIAR) was established to help other developing countries adopt these technologies.

The adoption of the Green Revolution technologies has led to substantial improvement in crop production and economic growth in the developing world. Vast research suggests that Green Revolution technologies contributed to a massive increase in crop production, food security, gross domestic product (GDP), real income per capita, demand for goods and services, new income and employment opportunities, stimulating the rural non-farm economy, and a decline in food prices, poverty, fertility, and child mortality across developing nations (Foster and Rosenzweig, 1996, Evenson and Gollin, 2003, Goltz *et al.*, 2020, Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021). For instance, in Asia, a 1% increase in the per hectare agricultural production led to a 0.48% reduction in poverty (Pingali, 2012). A 10-year delay of the Green Revolution in 2010 would have cost 17% of GDP per capita to the developing-world population, and the cumulative GDP loss would have been 83 trillion US dollars (Gollin *et al.*, 2021).

India was among the early adopters of the HYV crops around the mid-1960s and the adoption had significant variations based on factors like agro-climatic conditions, infrastructure, education, and other socioeconomic factors.[24] Climatic and environmental conditions, rain, networks of canal irrigation systems, and groundwater access significantly affected the adoption of the Green Revolution (D'Agostino, 2017, Bharadwaj *et al.*, 2020, Sekhri and

[22]Crop scientist Norman Borlaug began work on crop development in the 1940s, and for his efforts, he received the Nobel Peace Prize in 1970.

[23]Green Revolution is a series of complex innovations to make new crop varieties. One such innovation includes the fact that these high-yield varieties (HYV) were designed to be semi-dwarf so that they do not lodge (fall) when they grow tall enough like the traditional crops. Similarly, crops with other characteristics like disease resistance were developed. The HYVs of rice and wheat were more successful earlier due to vast preexisting scientific knowledge compared to other crops (Gollin *et al.*, 2021). However, these HYVs did not do better compared with the traditional varieties in the absence of enough fertilizers and water. Traditional varieties of rice and wheat were not 'tolerant' to fertilizers and water as the HYVs.

[24]Stagnation of agriculture during the colonial era, favoring industrial sectors over agricultural sectors post-independence, disastrous draughts, and sluggish land reforms were key reasons that India was on the verge of famine and set a stage for policymakers and donor agencies to invest in new technologies through the Green Revolution (Parayil, 1992).

Shastry, 2024, Asher *et al.*, 2022).[25] As discussed in Bharadwaj *et al.* (2020) in detail, due to the heavy canal irrigation networks during the colonial era in the northern states, and favorable conditions, HYVs were adopted earlier in the northern states, while the rest of the country relied primarily on rain, which can vary considerably based on agro-climatic conditions. Similarly, socio-economic factors like castes and wealth also played a major role in unequal access to the HYVs, with wealthy or large-scale landowners (typically belonging to higher castes) having higher access to the Green Revolution technologies than landless farmers and agricultural workers (typically belonging to lower castes) (Hurt, 2020).[26] Gender also played a part in the distribution of the HYVs and the benefits of the Green Revolution, with women farmers and female-headed households gaining proportionately less than men counterparts (Pingali, 2012).

India saw a massive improvement in various economic factors within the first few years of the Green Revolution. For instance, the adoption of HYV crops played a vital part in India's agriculture sector, which accounts for 23% of its GDP. From 1961 to 1970, cereal production increased by over 30% from 70 million tons to 93 million tons, and by 1999, it reached 186 million tons (Borlaug, 2002). Wheat and rice yields and cereal production doubled from 1970 to 1995, and cereal and calorie availability per person increased by 30%. Also, it is estimated that the 1% increase in the adoption of HYVs per hectare reduced poverty by 0.4% in the short run and 1.9% in the long run (Pingali, 2012). Further, child and infant mortality was considerably higher in India, and the Green Revolution helped decline child mortality by about 15 deaths per 1,000 children and succeeded in improving the health status of about 32 to 42 million preschool children (Evenson and Gollin, 2003, Bharadwaj *et al.*, 2020).

Although the Green Revolution had positive effects, a small body of literature also documents its adverse effects on the use of agrochemicals, health, ecology, and social equity in India. During the first two years of the Green Revolution in India, the consumption of nitrogenous fertilizer increased from about 658,000 metric tons to 1,196,000 metric tons

[25]Several other factors also contributed to the diffusion of the HYVs. For instance, a study found that radio broadcasts led to an increase in the adoption of the HYVs (Vasudevan, 2023). Similarly, crops' susceptibility to diseases and pests and the skills of farm workers also affected the adoption of the HYVs (Pingali *et al.*, 1996).

[26]Hurt (2020) describes that the education also played a role in adoption, since well-educated, usually large-scale farmers made better use of the supportive environment and multiple cropping. Even though the uniform benefits were not guaranteed, studies document that the Green Revolution also benefitted the poor through channels like a reduction in food prices and employment opportunities (International Food Policy Research Institute (IFPRI) Report 2002-03).

(Chakravarti, 1973). A study suggests that exposure to such massive agrochemicals in water increased infant and neonatal mortality and height-for-age and weight-for-age for children below age five, and the effects are most pronounced for poor women in rural areas (Brainerd and Menon, 2014). Similarly, a recent study indicates that exposure to the Green Revolution increases the likelihood of diabetes during mid-life for boys, primarily due to changes in dietary habits (Sekhri and Shastry, 2024). Other critics of the Green Revolution highlight the overuse and mismanagement of agrochemicals, loss of distinct indigenous crops, land infertility due to lack of crop rotation, loss of groundwater, and troubles of small farmers who sold their lands to large farmers due to increasing farm expenses and debt, creating a social inequity (Eliazer Nelson *et al.*, 2019).

# 3 Data

We evaluate whether early-life exposure to the adoption of Green Revolution technology affects long-term aging-related outcomes in India. To answer this question, we use data primarily from two sources, as mentioned below. We also use additional data from other sources described in this section.

## 3.1 Village Dynamics of South Asia (VDSA)

VDSA has the annual information on the area in hectares planted under high yield variant (HYV) for 281 districts and 19 states in India from 1966 to 2017.[27] The data on HYVs are for six major crops- rice, wheat, maize, finger millet, pearl millet, and sorghum. The data also includes annual information on the area and the production of 25 major and minor crops. We sum the area planted under the HYV crops in each district in the year of birth. We then divide this sum by the total area cultivated under all crops in each district in a year, which is our main treatment variable. This ratio gives us a share of the cultivated area planted under the HYV.[28]

Figure 2 shows the share of the total cultivated area planted under HYV for India from 1966 to 1989. As shown in the figure, the adoption of rice and wheat was rapid compared

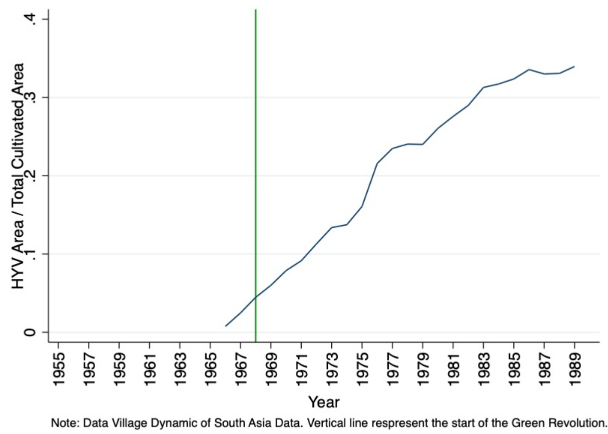
[27]These data are commonly used in the literature on the Green Revolution in India (e.g., Bharadwaj *et al.* (2020)).

[28]We remove a small number of observations if the total HYV area is greater than the total cultivated area.

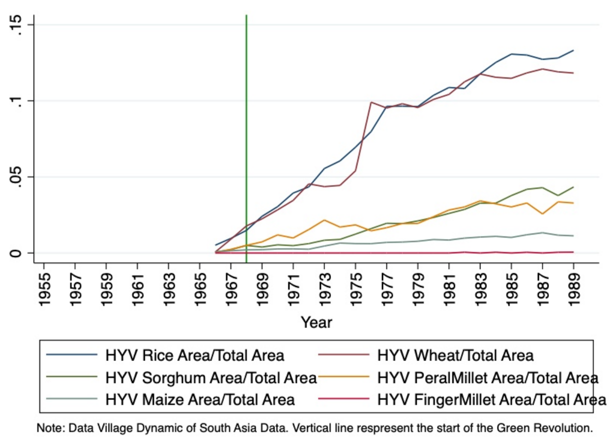
to that of the other HYV crops. Figure 3 describes the district-wise share of the high-yield crops from 1966 to 1989. This figure shows a substantial variation in the adoption of high-yield crops by various districts. As mentioned in detail in the previous section, the adoption was rapid in the northern states compared to the other parts of India. In our identification strategy, we explore these temporal and spatial variations in the adoption of the Green Revolution.

FIGURE 2: Share of Total Area Under High Yield Crops (by Year)

(a) High Yield Area Share- Combined

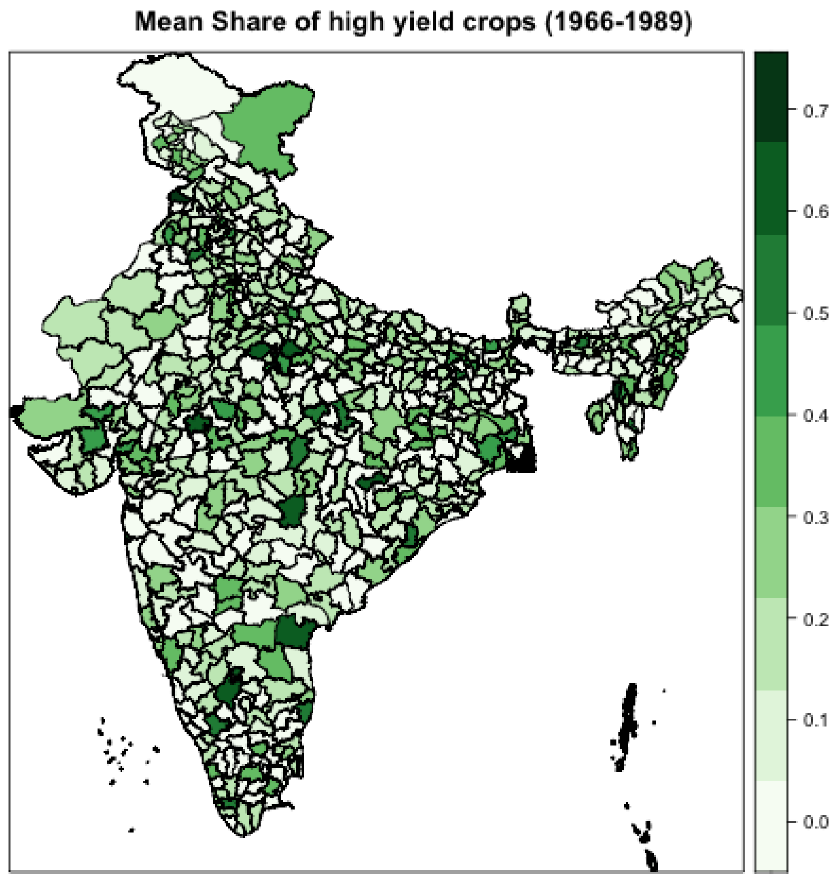



(b) High Yield Area Share- Separated




Note: This figure shows the trend in adopting HYV crops using VDSA data. The share of the total area under the Green Revolution (high-yield crops) is the ratio of area planted to high-yield crops to the total cultivated area (both in hectares) in an individual's birth district. Panel A shows the trend combined with all the HYV crops, and panel b shows the trend separately for each HYV crop.

FIGURE 3: Mean Share of High Yield Crops




Note: We merge LASI and VDSA data for the mean district share of HYV across all the birth cohorts from 1966 to 1989. We cross-walked the contemporary districts in LASI data, i.e., the 2011 Census with the 1961, 1971, and 1981 census.

## 3.2 Longitudinal Aging Study in India (LASI)

The LASI is the world's largest and India's first longitudinal aging study.[29] The LASI data are comparable to and harmonized with the Health and Retirement Study (HRS) in the United States. It is a nationally representative survey of over 72,000 older adults aged 45+ and their spouses (irrespective of age) above in 28 out of 29 States (except Sikkim) and 7 union territories in India. A survey for the first wave was conducted in 2017-19; the data was released in 2021. LASI is the first detailed scientific investigation of the health, social determinants, and economic well-being of older adults in India. More importantly, the data includes the respondents' birth district, which was virtually absent from any household surveys from the developing countries. We merge LASI and VDSA using the birth district

[29] Details on LASI's first wave can be found in Bloom *et al.* (2021).

and birth year.

Our primary sample includes respondents who were born from 1966 through 1974. We focus on this cohort since the Green Revolution started in India in 1966, and the youngest cohort of the LASI survey was born in 1974.[30] When we merge LASI data with the VDSA data using the birth district and birth year, we match almost all the districts in the VDSA data.[31] We have 281 districts that have experienced the Green Revolution since 1966, and the remaining 61 districts have not experienced it during our analysis period.

## 3.3 Other Data

In addition to the primary data, we use the following data. First, we use the 1961 Census for the pre-treatment census variables of sex ratio, the share of the rural population, and literacy rate. Secondly, we use the universe of the schooling data from the District Information System for Education (DISE) dataset, which is the 'most comprehensive information system in the education sector in India' (Ward, 2007). DISE is a school-level panel data of over 1.5 million schools in India. Each school is observed over time, starting from the year 2005. We use the 2015-16 wave of the DISE data. More importantly, DISE includes the school establishment year of each school, which we use to calculate the total number of schools in each district over time.[32]

[30] LASI is a nationally representative data of 45+ age group. And that's why our main sample is the 45+ age group. LASI also includes detailed data of the respondents' spouses irrespective of age, meaning some spouses could be below the 45+ age group (or born after 1974). However, we do not include them since the LASI data does not represent the population below 45.

[31] LASI data have the birth districts coded as per the 2011 Census. India had 640 districts in the 2011 Census and 397 districts in the 1961 Census. As the district boundaries changed over time from 1961 to 2011, we created a district crosswalk file from various sources, including Google Search, Census of India, and a crosswalk file generously provided by Aaditya Dar. Finally, We obtained the restricted data on the district of birth from the University of Southern California.

[32] DISE data covers school characteristics under different captions like school location, school management (public/ private), school categories (Primary, middle schools, secondary, high school), school facilities (building condition, availability of drinking water, library, toilets, playgrounds, computers, etc.), enrollment of boys and girls, teachers' information (number of teachers, teachers' qualification), etc. DISE covers enrollment from grades 1 to 8.

## 3.4 Outcome Variables

### 3.4.1 Cognitive Health

#### Summary

Our primary outcome variable, the 'general cognitive score,' is a general cognitive factor score representing the latent trait of the respondent's cognitive function (Flood *et al.*, 2022). The 'general cognition score' measures the respondent's overall cognitive ability, including latent factors of general cognitive function, memory, executive function, orientation, and language (Gross *et al.*, 2023, Livingston *et al.*, 2020). The score is harmonized with the Health and Retirement Study–Harmonized Cognitive Assessment Protocol (HRS-HCAP) from the United States, empirically reflects comparable domains of cognitive function among older adults across six countries, has high reliability, and is useful for population-based research (Gross *et al.*, 2023).[33] HRS is an ongoing national study of over 20,000 U.S. adults aged 51 and older. HRS-HCAP, a sub-study within HRS, specifically targets cognitive impairment and dementia in a representative sample of U.S. adults aged 65 and older. HCAP employs cognitive tests to assess various cognitive domains affected by aging, facilitating comparisons with other global studies (Langa *et al.*, 2020). This score is derived from latent variable modeling and using rich cognitive testing information from the population-representative LASI. One notable characteristic of this score is its insensitivity to including items that rely on literacy and numeracy. This aspect ensures that the score accurately reflects cognitive performance across individuals with varying literacy and numeracy levels. This is important since cognition is also intertwined with cultural practices and social contexts beyond literacy and numeracy (Rogoff, 2003).

#### Construction

The score is calculated in the following way, which includes LASI– Diagnostic Assessment of Dementia (LASI-DAD), which is a subset of the LASI data designed to offer a more precise estimation of dementia at the national level and to investigate key risk factors associated with

[33] The HCAP network represents the largest coordinated global initiative to date for conducting harmonized large-scale, population-representative studies on cognitive aging and dementia. The primary goal of the HCAP network is to offer standardized estimates of dementia and mild cognitive impairment prevalence on a global scale. By leveraging cross-national differences in essential risk and protective factors, the network aims to enhance our comprehension of the determinants of cognitive aging and dementia. The score is harmonized across aging studies from China, England, India, Mexico, South Africa, and the USA.

cognitive decline and dementia in India (Hu *et al.*, 2020).[34] LASI-DAD adopted the HCAP, with necessary modifications to suit the Indian context based on the higher illiteracy and innumeracy rates in India, as well as considering cultural nuances.[35] For instance, LASI-DAD was divided into literate (43·4%) and illiterate (56·6%) subgroups, and some tests were delivered as verbal instructions or cues instead of writing instructions for the illiterate individuals (Gross *et al.*, 2023). The 'general cognition score' is derived using a graded response item response theory (IRT) / confirmatory factor analysis (CFA) model outlined by (Muthén and Muthén, 2017), a well-established standard practice in the field of cognitive aging.[36] First, a CFA model for the general cognitive function was estimated in LASI-DAD (Gross *et al.*, 2020). The tests in the battery include broad domains of orientation, executive functioning, language/fluency, memory, and visuospatial, and five narrow domains of reasoning, attention/speed, immediate memory, delayed memory, and recognition memory. Appendix Figure 5 shows these domains and the correlations between each domain and the observed cognitive test items. Secondly, a CFA model for general cognitive functioning was estimated for the entire LASI sample. In this CFA, the model parameters of 11 comparable items between LASI-DAD and LASI were included, while the parameters of 42 unique items in LASI were freely estimated.[37] A statistical approach is shown in Vonk *et al.* (2022) for the cross-national harmonization of this cognition score in HRS-HCAP and LASI-DAD. Importantly, the score is scaled to have a mean of 0 and a variance of 1 within the LASI-DAD population because no natural scaling in latent variable space exists, ensuring comparability and consistency in measurement (Gross *et al.*, 2023).

[34] LASI-DAD study uses stratified, random sampling design for recruiting participants from the main LASI study and also oversamples participants with low cognitive function for the adequate sample size of the participant with dementia. Refer Gross *et al.* (2023), Flood *et al.* (2022) for more details.

[35] One example of such modification is that the tests were conducted in 19 different languages, given the vast diversity of the languages in India, which usually varies by the States. Another example of modification includes changing the names of persons and places from the original logical memory story recall test so that the Indian population can relate to it.

[36] IRT is a statistical framework used to analyze and interpret data from tests and questionnaires (Embretson and Reise, 2013). It is widely used in the field of psychology to measure various constructs such as intelligence, personality, and attitudes. IRT provides a more sophisticated approach to test analysis than classical test theory, as it takes into account the difficulty of individual test items and the ability of test-takers. This allows for more accurate and precise measurement of the construct being assessed. IRT has practical applications in education, clinical psychology, and market research, among other fields. It is a valuable tool for researchers and practitioners seeking to improve the quality and validity of their assessments.

[37] This approach of estimating parameters in one sample and fixing shared parameters to be equal in the second sample to create a link is referred to as 'item banking' (Gross *et al.*, 2023).

#### Validity

The general cognitive score is a validated and widely accepted method for evaluating cognitive health in observational and clinical research settings. The HCAP battery from the HRS has been successfully adapted in various countries, including the United States, England, Mexico, China, and South Africa (Gross *et al.*, 2020). A validated general cognitive score obtained from a neuropsychological test battery holds credibility in clinical samples and proves its relevance for clinically significant endpoints. Factor scores are increasingly being adopted as endpoints in clinical trials. The methodologies employed in test construction serve as the foundation for initiatives like the National Institute of Health (NIH) PROMIS and NIH Toolbox.

### 3.4.2 Cognitive Impairment

We use mild cognitive impairment (MCI) as another outcome, defined as the symptomatic pre-dementia stage defined by the U.S. National Institute on Aging guidelines (Langa and Levine, 2014). We follow the literature to define MCI as an indicator equal to 1 if the general cognition score is 1.5 standard deviations or below the education and age-matched mean for the main sample (Flood *et al.*, 2022, Kobayashi *et al.*, 2019). Since the sample in our study is relatively young (mean age is 49), MCI is the key outcome for measuring dementia.

### 3.4.3 Physical Health

We measure physical health outcomes by using the total number of chronic conditions as our key outcome variable. This measure is calculated by adding the positive responses to eight questions on 'ever had the following conditions: blood pressure, diabetes, cancer, lung disease, psych problems, arthritis, stroke, heart problems.'

## 3.5 Descriptive Statistics

We begin with descriptive evidence of the Green Revolution and the LASI cohort. Table 1 shows the characteristics of the 15,759 respondents in our sample. The mean age of the respondent is 49. The general cognitive score has a mean of 0.51 (SD 0.87), and about 7% of the sample had cognitive impairment. On average, the number of total chronic conditions is lower than 1; however, about 32% have some form of chronic conditions. About 58% of our

TABLE 1: Descriptive Statistics for Individuals Born from 1966 to 1974

| | Mean | SD | Min | Max | Obs |
|---|---|---|---|---|---|
| ***Green Revolution*** | | | | | |
| Treatment -1 to +2 | 0.12 | 0.12 | 0.00 | 0.71 | 14699 |
| Avg. Treatment Age -4,-3,-2 | 0.05 | 0.09 | 0.00 | 0.55 | 14698 |
| Avg. Treatment Age 3 to 5 | 0.18 | 0.15 | 0.00 | 0.77 | 14699 |
| Avg. Treatment Age 6 to 8 | 0.23 | 0.17 | 0.00 | 0.85 | 14699 |
| Avg. Treatment Age 9 to 11 | 0.27 | 0.19 | 0.00 | 0.90 | 14699 |
| Avg. Treatment Age 12 to 14 | 0.30 | 0.20 | 0.00 | 0.92 | 14699 |
| Avg. Treatment Age 15 to 17 | 0.32 | 0.20 | 0.00 | 0.92 | 14699 |
| Avg. Rain(mm) VDSA | 105.32 | 62.94 | 0.00 | 388.23 | 14699 |
| Avg.Max Temp(c) | 31.13 | 2.71 | 0.00 | 35.40 | 14699 |
| Avg.Min Temp(c) | 19.62 | 2.50 | -1.60 | 24.80 | 14699 |
| ***Individual Characteristics*** | | | | | |
| Cognition Score | 0.51 | 0.87 | -3.50 | 3.25 | 14647 |
| Langa-Weir (LW) Score | 13.85 | 4.76 | 0.00 | 27.00 | 14647 |
| Cognition Score>25 pct | 0.75 | 0.43 | 0.00 | 1.00 | 14647 |
| LW-Normal | 0.68 | 0.47 | 0.00 | 1.00 | 14647 |
| LW-CIND | 0.26 | 0.44 | 0.00 | 1.00 | 14647 |
| LW-Demented | 0.06 | 0.24 | 0.00 | 1.00 | 14647 |
| Word Recall | 9.99 | 3.36 | 0.00 | 20.00 | 14647 |
| Series 7 | 2.76 | 1.78 | 0.00 | 5.00 | 14647 |
| Word Recall >= 75pct | 0.22 | 0.42 | 0.00 | 1.00 | 14647 |
| Series7>=75pct | 0.27 | 0.44 | 0.00 | 1.00 | 14647 |
| Orientation | 7.15 | 1.22 | 0.00 | 8.00 | 14647 |
| Cognitive Impair | 0.07 | 0.26 | 0.00 | 1.00 | 14699 |
| Metabolic Syndrom Index | -0.04 | 0.54 | -0.35 | 3.70 | 14653 |
| Fertility | 5.19 | 2.42 | 1.00 | 21.00 | 14465 |
| Height (Stdz.) | 0.06 | 0.99 | -4.37 | 4.45 | 13265 |
| BMI | 23.44 | 4.74 | 10.52 | 63.41 | 13271 |
| Overweight | 0.34 | 0.47 | 0.00 | 1.00 | 13271 |
| Obese | 0.09 | 0.29 | 0.00 | 1.00 | 13271 |
| Total Chronic Conditions | 0.43 | 0.70 | 0.00 | 6.00 | 14699 |
| Any Chronic Condition | 0.33 | 0.47 | 0.00 | 1.00 | 14699 |
| Ever had Diabetes | 0.09 | 0.28 | 0.00 | 1.00 | 14646 |
| Ever had High BP | 0.20 | 0.40 | 0.00 | 1.00 | 14648 |
| Ever had Heart Problems | 0.02 | 0.13 | 0.00 | 1.00 | 14652 |
| Attended School | 0.59 | 0.49 | 0.00 | 1.00 | 14699 |
| Above Primary Edu | 0.35 | 0.48 | 0.00 | 1.00 | 14699 |
| Childhood Finance Poor | 0.40 | 0.49 | 0.00 | 1.00 | 14549 |
| Birth Year | 1969.50 | 2.20 | 1966 | 1974 | 14699 |
| Latest Age | 48.06 | 2.18 | 45 | 55 | 14699 |
| Male | 0.45 | 0.50 | 0.00 | 1.00 | 14699 |
| Birth Rural | 0.50 | 0.50 | 0.00 | 1.00 | 14699 |
| Father Went School | 0.33 | 0.47 | 0.00 | 1.00 | 14699 |
| Mother Went School | 0.14 | 0.35 | 0.00 | 1.00 | 14699 |
| Scheduled Caste (SC) | 0.19 | 0.40 | 0.00 | 1.00 | 14615 |
| Scheduled Tribe (ST) | 0.10 | 0.30 | 0.00 | 1.00 | 14615 |
| Other Backward Class (OBC) | 0.43 | 0.50 | 0.00 | 1.00 | 14615 |
| Other Caste/Not Reported | 0.28 | 0.45 | 0.00 | 1.00 | 14615 |
| SC,ST,OBC | 0.72 | 0.45 | 0.00 | 1.00 | 14699 |
| ***1961 Census*** | | | | | |
| Share Literate(age10 above) | 0.30 | 0.14 | 0.00 | 0.72 | 14699 |
| Share Rural Population | 0.79 | 0.23 | 0.00 | 1.00 | 14699 |
| Sex Ratio M/F | 1.06 | 0.20 | 0.00 | 1.63 | 14699 |
| Observations | 14699 | | | | |

Note: The table shows the summary statistics of the respondents from the first wave of the Longitudinal Aging Study in India (LASI) for the 45+ age group (born from 1966 to 1974). We merged Village Dynamics in South Asia (VDSA) data with LASI data using the birth district and birth year of the LASI respondents with 314 districts at that time. Refer to the text for the variable definitions.

sample is Women, and about half of the respondents were born in rural areas. On Average, one-third of the respondents have education above the primary level, and 42% never attended school. The fathers of the respondents are more than twice as likely to attend school than their mothers, given the social stigma about women's education in India. Almost 72% belong to lower castes.[38] The average exposure to the Green Revolution from in-utero to age 2 was 12 %.

## 4 Estimation Strategy

We study the long-term effect of early-life exposure to the Green Revolution. We follow (Bharadwaj *et al.*, 2020) to use a proxy for the Green Revolution as the share of the total area planted under high-yield crops.[39] In the basic specification, we use the ordinary least square (OLS) to estimate the following equation.

$$Y_{isdt} = \sum_{\tau=-4,\tau\neq-1}^{17} \beta_\tau HYV_{\tau(d,t)} + X'_{isdt}\gamma + \delta_t + \mu_d + \tau_{st} + \varepsilon_{isdt} \tag{1}$$

where $Y_{idt}$ is the health outcomes of individual $i$, born in district $d$ of state $s$ at year $t$. The measure of exposure to the Green Revolution is $HYV_{d,t}$, which is the share of the total area planted under high-yield crops in the birth district $d$ at the birth year $t$. We include the exposure to the treatment over the early life cycle from pre-birth (4 years before the birth to 2 years before), around the birth (in-utero to age 2), and early childhood life period (age 3 to 5, age 6 to 8, age 9 to 11, age 12 to 14, and age 15 to 17). We average the treatment in these categories primarily to account for the potential measurement error in reporting the birth year. We include birth district fixed effects $\mu_d$ that control for all the time-invariant characteristics of the district. We also include birth year fixed effects $\delta_b$ that control for the time-specific shocks affecting all the districts in the year of birth. We add a vector of controls, $X'$, that includes average rainfall, temperature, gender, castes, an indicator if the respondent was born in a rural area, and an indicator if the father and mother went to school. We also control for the pre-treatment 1960 census variables- sex ratio, the share

[38]We define 'lower castes' if the respondent belongs to either Scheduled Castes (SC), Scheduled Tribes (ST), or Other Backward Classes (OBC). The share of the SC, ST, and OBC population closely matches with the share from different sources, including the Census 2011 (Pew Research Center, 2021).

[39]Our specification is also similar to a study on the effect of weather shock on cognition in a similar context (Webb, 2024).

of the rural population, and literacy rate. Additionally, we also include birth state-specific linear time trends ($\tau_s.t$) or birth state-by-year fixed effects ($\tau_{st}$). The first takes into account any unobserved trending variables that may vary by state-specific cohorts and the second accounts for any annual pattern in later life outcomes that may differ across states. Standard errors are clustered at the district of birth level.

For identification, we compare individuals from the same district who were exposed to varying levels of high-yield crops based on their years of birth, over and above any unobserved shocks to the cognition scores that vary by year of birth and any long-run trends (or annual pattern) in that individual's state (or region) of birth. The estimate $\beta$ is the consistent estimate of exposure to the Green Revolution if, conditional on the district and birth-year fixed effects and controls, changes in the district-level yield of HYV crops are not correlated with other factors that also affect long-term health. Our study's primary analysis period is from 1966 to 1974, since the Green Revolution period is considered to have begun in about 1966, and the youngest cohort of the LASI respondents was born in 1974.

# 5 Results

## 5.1 Main Results

In this section, we present our main findings. Panel (A) and Panel (B) of Table 2 show the effect of in-utero to age 2 exposure to the high yield varieties (HYV) on later life cognitive function and the number of chronic conditions, respectively. The first columns in each panel show estimates for the specification with birth-district and birth-year fixed effects. In the second column of both panels, we include four types of control variables- individual-level time-invariant, parental education, weather, and the 1961 Census characteristics. For individual controls, we include gender and caste; for weather controls, we include average rainfall and temperature; for parental controls, we include indicators that the father and mother went to school; and for the pre-treatment census variables, we include sex ratio, the share of the rural population, and literacy rate from the 1960 Census. In the third column, we add state-specific linear time trends to account for possible unobserved trending variables that may vary by state-specific cohort. In our preferred specification, in the fourth column, we replace state-specific linear time trends with state-by-birth-year fixed effects to control for the annual variation in health outcomes that may vary across states. Our preferred specification controls for unobserved heterogeneity across different states, given the massive heterogeneity in states in India in terms of language, culture, education level, and agricultural practices. By including fixed effects for each state, we account for any unobserved factors that might vary across states but remain constant over time. Similarly, state-by-birth-year fixed effects capture the nonlinear patterns in the data, while linear trends might not be able to capture the underlying dynamics in the data.

TABLE 2: Effect of early life exposure to the HYV on cognitive and physical health

| | Panel (A) Outcome: General Cognition Score | | | | Panel (B) Outcome: Total Chronic Conditions | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Variables | | | | | | | | |
| Pre-Conception | 0.196 | 0.131 | 0.167 | -0.005 | 0.243 | 0.217 | 0.285 | 0.369 |
| | [0.179] | [0.180] | [0.201] | [0.272] | [0.152] | [0.172] | [0.219] | [0.257] |
| Treatment -1 to +2 | 0.072 | 0.037 | 0.169 | 0.489* | -0.012 | 0.053 | 0.226 | 0.239 |
| | [0.199] | [0.169] | [0.197] | [0.253] | [0.219] | [0.216] | [0.263] | [0.311] |
| Observations | 14,636 | 14,636 | 14,636 | 14,646 | 14,688 | 14,688 | 14,688 | 14,698 |
| R-squared | 0.141 | 0.334 | 0.335 | 0.344 | 0.069 | 0.082 | 0.084 | 0.094 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y | Y |
| Controls | | Y | Y | Y | | Y | Y | Y |
| State-Birth Y Trend | | | Y | | | | Y | |
| State-Birth Y FE | | | | Y | | | | Y |
| Mean of Y | 0.525 | 0.525 | 0.525 | 0.525 | 0.402 | 0.402 | 0.402 | 0.402 |

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later life cognitive function (panel A) and the total number of chronic conditions (panel B) using Equation 1. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave of the Longitudinal Aging Study in India (LASI). Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Column 1 in Table 2 shows that early-life exposure to the Green Revolution affects later-life cognitive function positively; however, the estimates are statistically insignificant. The estimates on the pre-conception are also statistically insignificant, suggesting evidence of the fulfillment of the parallel trend assumption. In column 2, we introduce controls, and the estimates decline by half; however, they are still insignificant. In column 3, with the state-by-birth-year trends, we also do not find a significant effect. Finally, column 4 of Table 2, which is our preferred specification with state-by-birth-year fixed effects, suggests that one standard deviation (SD) increase in the average HYV share during in-utero to age 2 improves the cognitive score by 0.058 (coefficient X SD) and the estimate is statistically significant at 10% level.[40] These effects can (loosely) be comparable with a recent study which finds a one SD improvement in weather conditions during age two leads to an improvement in cognition during adulthood (aged 16-37) by 0.063 SDs in a comparable developing country (Webb, 2024). In Appendix Table 9, we also show the estimates with the full age profile from pre-conception to age 17.[41] We also show results with the results on 'cognition impairment' in Appendix Table 10, which shows that the direction of the effect is as expected. However, the effect is not statistically significant.

In panel (B), we show the effects on later life physical health, using the total number of chronic conditions as an outcome. In our preferred estimates in column 8, we find that early life exposure (in-utero to age 2) to the Green Revolution increases the total number of chronic conditions; however, the estimates are not statistically significant. To explore further, we provide evidence of the effects of heterogeneous treatment in the next section.

## 5.2 Heterogeneity Analysis

We explore various heterogeneity in the effect of early life exposure to the Green Revolution on later-life cognitive function in Table 3. We mainly explore the treatment effects based on gender, caste, and region for various reasons. First, stronger gender norms exist in India, with usually higher intra-household resources such as food, nutrition, and education investments in early life allocated for males than females. Research also suggests that the Green Revolution reduced infant mortality among males more than females, suggesting potentially other biological factors that may differ by gender (Goltz *et al.*, 2020, Bharadwaj *et al.*, 2020). Such stark gender disparities are also evident in the cognition score, with men having significantly higher scores (0.79) than women (0.27). Secondly, caste-based disparities are deeply entrenched in Indian society, with historical discrimination against socially disadvantageous groups often excluding them from societal resources and opportunities. have significant implications for access to societal resources and health outcomes. The higher castes have significantly higher cognition scores (0.75) compared to Scheduled Castes (0.29), Scheduled Tribes (0.09), or Other Backward Classes (0.54). Examining how the Green Revolution

[40] The estimate = 0.489 X SD of the treatment variable.

[41] We find that in-utero to age 2 exposure to the Green Revolution positively affects later-life cognitive function; however, the estimates are not statistically significant.

influenced health outcomes across caste groups helps identify and address inequalities in agricultural development and healthcare provision. Finally, rural areas often bear the brunt of agricultural changes, yet they may also benefit from increased agricultural productivity since agriculture is usually saturated around rural areas. Understanding how the Green Revolution affected health outcomes in rural versus urban areas provides insights into the broader implications of agricultural transformations on public health and informs policies to improve rural healthcare infrastructure and services.

First, we do not find any statistically significant effects on cognitive function among men and women (columns 1 and 2), even though the coefficients are positive and large. Secondly, we find a statistically significant increase in cognitive function among the low-caste respondents (column 3).[42] Specifically, a one SD increase in the average HYV share during in-utero to age 2 improves the cognitive score by 0.083 SD among lower castes. There are two possible explanations for the positive effects on lower castes. First, the lower caste households are more likely to be poorer and usually lack the financial and nutritional resources to invest in a child's development. Generally, low castes are significantly less likely to attend school, have less educated parents, are less likely to stay in literate population areas, and are more likely to reside in rural areas. With access to some of the resources through the Green Revolution, one might expect improvement in the financial and nutritional resources for the low castes.[43] This evidence is consistent with the literature suggesting better outcomes of the Green Revolution for low castes, like reduced child mortality and increased access to health facilities (Bharadwaj *et al.*, 2020, Munshi and Rosenzweig, 2009). The second explanation is about an increase in education among low castes, which we explore more the mechanism section 6.

Further, results show a statistically significant increase in cognitive function among responders born in rural areas (column 5). Specifically, a one SD increase in the HYV share during in-utero to age 2 improves the cognitive score among rural born by 0.104 SD. The positive benefits of the Green Revolution for rural areas may imply that the benefits of the

[42] The data do not include the castes categories for the high castes, so we cannot say anything about the results on high castes.

[43] The increased production resulting from the Green Revolution (GR) has effectively reduced food prices (Evenson and Gollin, 2003). Since the poor (more likely from the lower castes) spend a greater share of their income on food than the rich (more likely from the higher castes), the price reduction might expand the budget constraints for the lower castes. This shift in budgetary dynamics could potentially allow them to allocate a higher share of their income than before to invest in their children's human capital development, which may affect later life cognitive health.

TABLE 3: Heterogenous Treatment Effect

| | Outcome Variable: General Cognition Score | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Castes | Women Low Castes |
| Pre-conception | -0.267 | 0.189 | -0.156 | 0.008 | -0.057 | 0.072 | -0.002 |
| | [0.390] | [0.298] | [0.294] | [0.422] | [0.294] | [0.421] | [365] |
| In-utero to Age 2 | 0.568 | 0.466 | 0.698** | 0.331 | 0.963*** | 1.166*** | 0.735* |
| | [0.362] | [0.356] | [0.291] | [0.358] | [0.358] | [0.413] | [0.420] |
| Observations | 6,540 | 8,067 | 10,515 | 7,352 | 7,248 | 5,196 | 5,823 |
| R-squared | 0.287 | 0.325 | 0.343 | 0.323 | 0.377 | 0.380 | 0.308 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.739 | 0.185 | 0.440 | 0.662 | 0.327 | 0.249 | 0.090 |

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later life cognitive function using Equation 1, separately estimated for each group. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Green Revolution were mediated through agricultural income and rural development. This evidence is also consistent with the literature suggesting the benefit of the Green Revolution in reducing child mortality in rural areas (Bharadwaj *et al.*, 2020). Finally, the positive effects on the cognitive function of the Green Revolution are strongest for the low castes born in rural areas (column 6), i.e., an increase in general cognitive function by 0.123 SD. In section 6, we show some of the potential channels for these positive gains in cognitive function.

We also show the results of heterogeneous treatment effects on another measure of cognition, i.e., cognition impairment. Table 4 suggests that the men and respondents born in rural areas have significantly less likelihood of cognitive impairment. We find the direction of effect for the low castes as expected, but the effect is not statistically significant. These results provide evidence that early life exposure to the Green Revolution also benefitted men and rural areas by decreasing the occurrence of cognitive impairments. Finally, in Appendix subsection C.3, we show and explain in detail the heterogeneous treatment effects of the Green Revolution on the physical outcomes of any chronic conditions, diabetes, and Body Mass India (BMI).[44]

[44] We are also working on including the overweight and obesity as outcomes.

TABLE 4: Heterogenous Treatment Effect

| | Outcome Variable: Cognitive Impairment | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Castes | Women Low Castes |
| Pre-conception | 0.080 | -0.113 | 0.108 | 0.006 | 0.110 | 0.041 | 0.059 |
| | [0.087] | [0.214] | [0.090] | [0.129] | [0.156] | [0.211] | [0.213] |
| In-utero to Age 2 | -0.265*** | 0.121 | -0.097 | -0.077 | -0.211* | -0.061 | 0.097 |
| | [0.089] | [0.134] | [0.157] | [0.114] | [0.111] | [0.131] | [0.157] |
| Observations | 6,566 | 9.093 | 10,554 | 7,387 | 7,265 | 5,210 | 5843 |
| R-squared | 0.102 | 0.103 | 0.103 | 0.101 | 0.111 | 0.140 | 0.130 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.044 | 0.093 | 0.067 | 0.048 | 0.084 | 0.088 | 0.096 |

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later-life cognitive impairment using Equation 1, separately estimated for each group. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

# 6 Mechanism

In subsection 5.2, we find the heterogeneous treatment effect of the early life exposure to the Green Revolution on the later life cognitive function, mainly for the low-castes and rural areas. We unpack some of the channels through which this effect may exist. First, we test whether better cognition mediates through better nutrition by using 'height' as a proxy, which is one of the predictors for better early life investments. Secondly, we study whether education contributes to better cognitive function. Finally, we study school construction as one of the mediators to rule out if the construction of schools was driving some of the positive effects.

## 6.1 Height

We test whether early life exposure to the Green Revolution also affects other later life health outcomes that may explain the benefits in the positive cognitive function. We study height as one of the outcomes. We standardized the height based on gender. The estimates are documented in Table 5.

If the Green Revolution helped the weakest survive, one would expect those people to

TABLE 5: Heterogenous Treatment Effect on Height

| | Outcome Variable: Standardized Height | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Castes | Women Low Caste |
| Pre-conception | -0.011 | -0.144 | 0.041 | 0.385 | -0.614 | -0.346 | -0.290 |
| | [0.637] | [0.444] | [0.531] | [0.613] | [0.553] | [0.686] | [0.508] |
| In-utero to Age 2 | 0.847 | -0.741 | 0.295 | -0.017 | 0.336 | -0.299 | -0.359 |
| | [0.644] | [0.534] | [0.469] | [0.675] | [0.590] | [0.712] | [0.640] |
| Observations | 5,868 | 7.354 | 9,624 | 6,607 | 6,611 | 4,786 | 5,363 |
| R-squared | 0.164 | 0.143 | 0.118 | 0.150 | 0.160 | 0.167 | 0.165 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.030 | 0.032 | -0.018 | 0.028 | 0.034 | -0.004 | 0.006 |

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on height using Equation 1, separately estimated for each group. The outcome variable is the standardized height based on gender. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

have worse health outcomes. We do not find evidence that early-life exposure to the Green Revolution affects later-life height for any group. This evidence is also consistent in the literature that suggests the Green Revolution does not affect heights among children (Bharadwaj *et al.*, 2020).[45]

## 6.2 Education

Since education is profoundly related to later-life cognition[46], we test whether the subgroups' cognitive function improvement is attributed to education. We use outcome on education as an indicator that takes the value of 1 if the respondent attended any school and 0 otherwise. Table 6 shows the estimates of early life exposure to the Green Revolution on education. The magnitudes in columns 3 and 8 show significant improvement in the likelihood of attending school for low-castes (10% level) and low-castes born in rural areas (1% level). Further, in Appendix Figure 7, we show the results with the full age profile for the different groups. We find that early life exposure to the Green Revolution significantly improved the likelihood of attending school among these groups. Importantly, the effect is higher and more significant

[45]This evidence is also consistent with a study with similar context from other developing country (Webb, 2024).

[46]Angel *et al.* (2010)

during the Green Revolution exposure around birth and during the age of 9-11. Using another nationally representative data from India, we provide distributions in Figure 8 of the education levels in low-caste people born during the pre and post-Green revolution period, which provides some evidence that the share of the sample who completed primary education among lower castes was higher in post-Green revolution period. [47]

TABLE 6: Heterogenous Treatment Effect on Schooling

| | Outcome Variable: Attended School | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Caste | Women-Lowcaste |
| Pre-conception | -0.029 | -0.076 | 0.009 | 0.079 | -0.084 | -0.217 | -0.153 |
| | [0.236] | [0.174] | [0.158] | [0.224] | [0.196] | [0.229] | [0.171] |
| In-utero to Age 2 | 0.061 | 0.322 | 0.324* | -0.023 | 0.365 | 0.744*** | 0.593*** |
| | [0.258] | [0.205] | [0.188] | [0.245] | [0.226] | [0.244] | [0.214] |
| Observations | 6,566 | 8,093 | 10,554 | 7,387 | 7,265 | 5,210 | 5,843 |
| R-squared | 0.249 | 0.385 | 0.329 | 0.294 | 0.394 | 0.403 | 0.377 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.677 | 0.396 | 0.510 | 0.630 | 0.480 | 0.416 | 0.319 |

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on schooling using Equation 1, separately estimated for each group. The outcome variable is whether the respondent went to school or not. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

## 6.3 Construction of Schools

We further explore one of the first pieces of evidence on whether the Green Revolution also affected the building of more schools to explain whether the positive gain in cognitive functions was driven by the construction of schools. We use the universe of the school administration data for the year 2015-16, which has information on over 1.5 million schools in India in 2015-16, including the school construction years.[48] We merged VDSA data with DISE data using the district and year of construction. We cross-walked the districts from DISE data in 2015-16 to the 1960s districts to match with the VDSA data. Figure 4 shows the adoption of the HYVs and the cumulative number of schools in India.

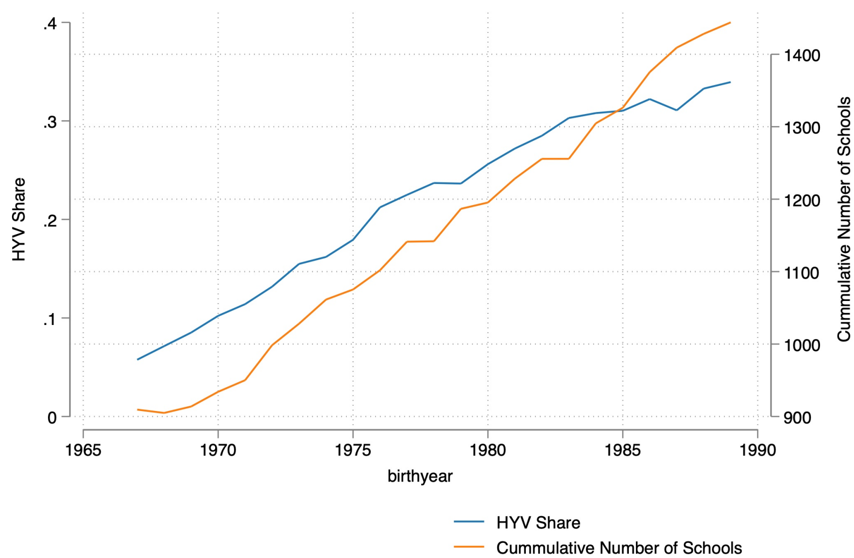
[47]We use the India Human Development Survey (IHDS) wave 2011-12.

[48]The data goes back to schools constructed in the 1850s.

For the analysis, we restrict the sample period to 1966-1989. The primary treatment is the same as before, i.e., the share of HYV crops. The outcome variables are the total number of schools in a district in a given year in all the above categories. We also calculate the rural and urban schools in each of these categories. We control for the 1961 census district-level share of literate aged 5+ population, share of the rural population, and male-female ratio; for each, we include the linear time trend.

The results are shown in Table 7 for school constructions in rural areas. Our preferred specification in column 3 with birth-state-by-year fixed effects suggests that the increase in the adoption of HYVs did not significantly affect the construction of the school. This evidence rule out that the school construction did not drive the gain in education and cognitive function, especially among the rural population.

FIGURE 4: Green Revolution and Number of Available Schools




Note: We merge DISE and VDSA data using the district and year. The cumulative number of schools is the average of the cumulative number of schools in each district in India.

## 6.4 Financial Condition as Growing Up

Further, we find evidence on whether early life exposure to the HYVs under the Green Revolution affects the financial conditions while growing up. LASI survey asks questions about the self-rated family financial situation before age 16 in three categories: pretty well

TABLE 7: Effect of the Green Revolution on Rural School Construction

| VARIABLES | (1)<br>Rural Schools | (2)<br>Rural Schools | (3)<br>Rural Schools |
|---|---|---|---|
| HYV Area / Cultivated Area | -14.74*** | -4.58 | -0.88 |
| | [5.08] | [4.41] | [4.78] |
| Observations | 6,968 | 6,968 | 6,968 |
| R-squared | 0.29 | 0.32 | 0.53 |
| District FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Census Controls | Yes | Yes | Yes |
| Mean of dependent variable | 21.79 | 21.79 | 21.79 |
| State-Year Trend | | Yes | |
| State-Year FE | | | Yes |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows the effect of the Green Revolution on the cumulative number of schools constructed. We merged Village Dynamics in South Asia (VDSA) data with DISE data using district and year from 1966 to 1989. We control for the 1961 census district-level share of literate aged 5+ population, share of the rural population, and male-female ratio; for each, we include the linear time trend.

off, average, and poor. We create an indicator variable equal to 1 if the financial condition was poor and 0 if it was either pretty well off or average. The results are shown in Table 8, showing the statistically significant improvement in financial conditions (decline in the 'poor financial condition') for the lower castes respondents (Column 3). We find improvement in financial condition for other beneficiary groups like respondents born in rural areas (column 6) and lower castes born in rural areas (column 8). However, the estimates are not statistically significant.

TABLE 8: Effect of Early Life Exposure to the HYV on Financial Condition while Growing Up

| | Outcome Variable: Childhood Financial Condition was 'Poor' | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Caste | Women-Lowcaste |
| Pre-conception | 0.089 | 0.216 | 0.219 | 0.071 | 0.134 | -0.023 | 0.245 |
| | [0.218] | [0.233] | [0.202] | [0.227] | [0.235] | [0.329] | [0.282] |
| In-utero to Age 2 | -0.274 | -0.056 | -0.438** | -0.173 | -0.000 | -0.053 | -0.307 |
| | [0.266] | [0.204] | [0.191] | [0.252] | [0.256] | [0.325] | [0.241] |
| Observations | 6,495 | 8,014 | 10,446 | 7,306 | 7,195 | 5,159 | 5,783 |
| R-squared | 0.216 | 0.212 | 0.197 | 0.233 | 0.203 | 0.221 | 0.226 |
| Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.451 | 0.404 | 0.456 | 0.426 | 0.442 | 0.459 | 0.430 |

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent had poor financial condition while growing up. The outcome variable is 1 if the financial condition was poor and 0 if the financial condition was either average or pretty well off. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). The outcome variable takes value 1 if the respondent reported of having any chronic condition and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

# 7 Robustness

To examine the robustness of main estimates, we perform several robustness checks. First, we include different specifications in our main results in Table 2. For instance, we control for observable characteristics like weather conditions, parental education, gender, and castes, as well as district-level characteristics from the Census, such as literacy rate, gender ratio, and share of rural population. We include the fixed effects of birth district and birth year to address the temporal and spatial factors associated with adopting the HYV, which might also affect health later in life. Alternatively, we include birth state-specific linear time trends or birth state-by-year fixed effects.[49] In these specifications, the direction of the effects remains the same.

Secondly, in Appendix Table 9, we show the estimates on the full age profile from in utero to age 17. In this table, we show the effect of the Green Revolution on later-life cognitive function at different stages of childhood. In column 4, the estimate of exposure to the treatment in utero to age 2 (0.375) is similar in magnitude to the estimate (0.416) in Table 2. Similarly, for our key heterogeneous treatment effects based on castes and regions, our estimates in Table 3 replicate the significant positive effect on cognitive function when we include a full age profile in Appendix Figure 6.

Further, our estimates might suffer from differential survival bias if only the weakest kids survived after the Green Revolution. To account for the survival bias, we drop the bottom 5 percentile sample in the distribution of the gender-adjusted height.[50] We show the results in Table 14 for our preferred specification using Equation 1. We observe a reduction in the coefficients related to our primary treatment variables compared to the main results presented in Table 2. Nevertheless, the standard errors remain largely unchanged, suggesting our estimates' precision has not been affected after excluding the bottom 5th percentile of the sample.

# 8 Conclusion & Discussion

We contribute to the vast literature on the Green Revolution by studying its unexplored long-term impacts on aging-related cognitive and physical health outcomes, focusing on cognitive function, cognitive impairments, and chronic conditions, using the largest aging data in the world from India. We find that in-utero to age 2 exposure to the Green Revolution among 45 to 54 age groups improves the later-life general cognitive function, with stronger effects for the socially disadvantaged group (lower caste) and individuals born in rural areas, with the highest effects for the lower castes born in rural areas. For men, rural-born, and higher caste individuals, we also find a significant decline in the likelihood of mild cognitive impairment, which is considered the pre-dementia stage. On the other hand, we also find evidence of an

[49] The first takes into account any unobserved trending variables that may vary by state-specific cohorts, and the second accounts for any annual pattern in later life outcomes that may differ across states.

[50] This cut-off is motivated by a study that finds that the Green Revolution reduces child mortality by 5.1% (Bharadwaj *et al.*, 2020).

increase in chronic conditions, primarily for men and people born in urban areas.

Our findings suggest that the demand side factors primarily drive the positive gains in cognition. We find that the significant improvement in attending schools explains the cognitive gains for low-caste and rural-born individuals. We do not find evidence that supply-side factors like school construction were driving these positive gains in the general cognitive function. Our results also rule out that the improvement in early-life nutrition drove these factors since we did not find any improvement in age-adjusted height, suggesting other evidence that the income effects play a significant role.

Regarding policy, our estimates suggest that the Green Revolution has the potential for long-term benefits in aging-related outcomes like cognition and ADRD; however, it has some negative effects in chronic conditions. These findings are important from a policy perspective since the Green Revolution is an ongoing policy in developing countries, especially in the African regions, and we need to understand whether to keep investing in these policies. In particular, the Alliance for a Green Revolution in Africa (AGRA) was established in 2006 by former UN Secretary-General Kofi Annan to promote Green Revolution technologies in African countries (Carter *et al.*, 2021). Our findings highlight the potential benefits and costs of adopting the HYVs. We hope future research will focus on understanding whether these benefits and costs of the Green Revolution for India also translate to African countries and other under-adopted countries.

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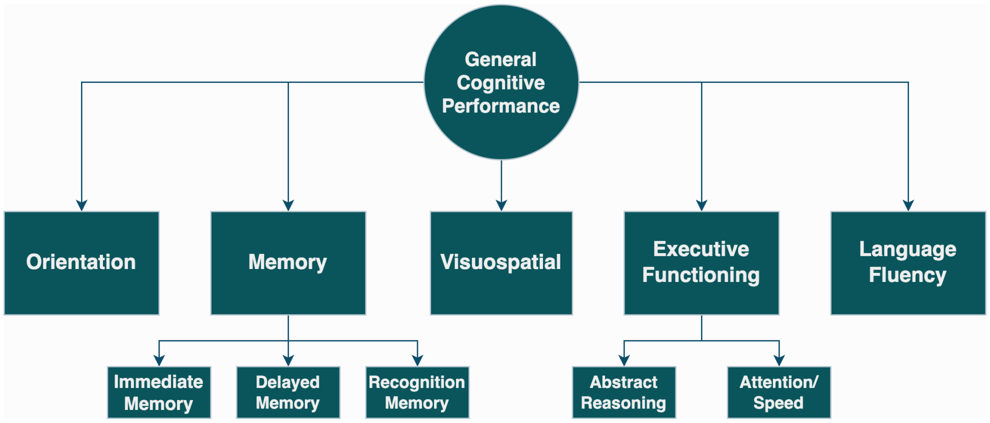
# Appendices

## A Data

FIGURE 5: Components of the cognition score




Note: This framework shows the broad components of the cognition score, as documented in Gross *et al.* (2020). 'Orientation' includes assessing orientation to time (e.g., name the current month and year) and place (e.g., city or state). 'Memory' tests include tests such as recalling a 3-word and 10-word list and names and places from a short story. 'Visuospatial' tests include recall of the drawings like interlocking pentagons and constructional praxis. 'Executive function' tests include tests like Raven progressive matrices task, drawing of a clock, go/no-go tests, numeracy tasks, and backward day counting. Finally, 'language fluency' includes tests like animal naming, writing or saying a sentence, naming common objects by sight, and pointing to a window and a door.

## B Results

TABLE 9: Effect of Early Life Exposure to the Green Revolution on the Cognition Score (Full Age Profile)

| | Outcome Variable: General Cognition Score | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Variables | | | | |
| Pre-Conception | 0.270 | 0.172 | 0.145 | -0.124 |
| | [0.174] | [0.169] | [0.191] | [0.255] |
| In-utero to Age 2 | -0.040 | 0.015 | 0.114 | 0.464* |
| | [0.206] | [0.172] | [0.189] | [0.242] |
| Avg. Treatment Age 3 to 5 | 0.406 | 0.207 | 0.168 | 0.221 |
| | [0.275] | [0.231] | [0.253] | [0.299] |
| Avg. Treatment Age 6 to 8 | -0.374* | -0.523*** | -0.516** | -0.746*** |
| | [0.215] | [0.198] | [0.219] | [0.268] |
| Avg. Treatment Age 9 to 11 | 0.078 | -0.096 | -0.101 | 0.148 |
| | [0.333] | [0.297] | [0.314] | [0.338] |
| Avg. Treatment Age 12 to 14 | -0.303 | -0.412 | -0.250 | -0.073 |
| | [0.329] | [0.282] | [0.306] | [0.270] |
| Avg. Treatment Age 15 to 17 | 0.164 | 0.118 | 0.104 | 0.112 |
| | [0.220] | [0.189] | [0.211] | [0.224] |
| | | | | |
| Observations | 14,636 | 14,636 | 14,636 | 14,646 |
| R-squared | 0.142 | 0.334 | 0.335 | 0.345 |
| Birth year FE | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y |
| Mean of Y | 0.525 | 0.525 | 0.525 | 0.525 |
| Controls | | Y | Y | Y |
| State-Birth year FE | | | | Y |
| State-Birth year Trend | | | Y | |

Note: This table shows the effect of early life exposure to the Green Revolution on later life cognitive function. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). The outcome variable is the general cognitive score. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 10: Effect of early life exposure to the HYV on the cognitive impairment

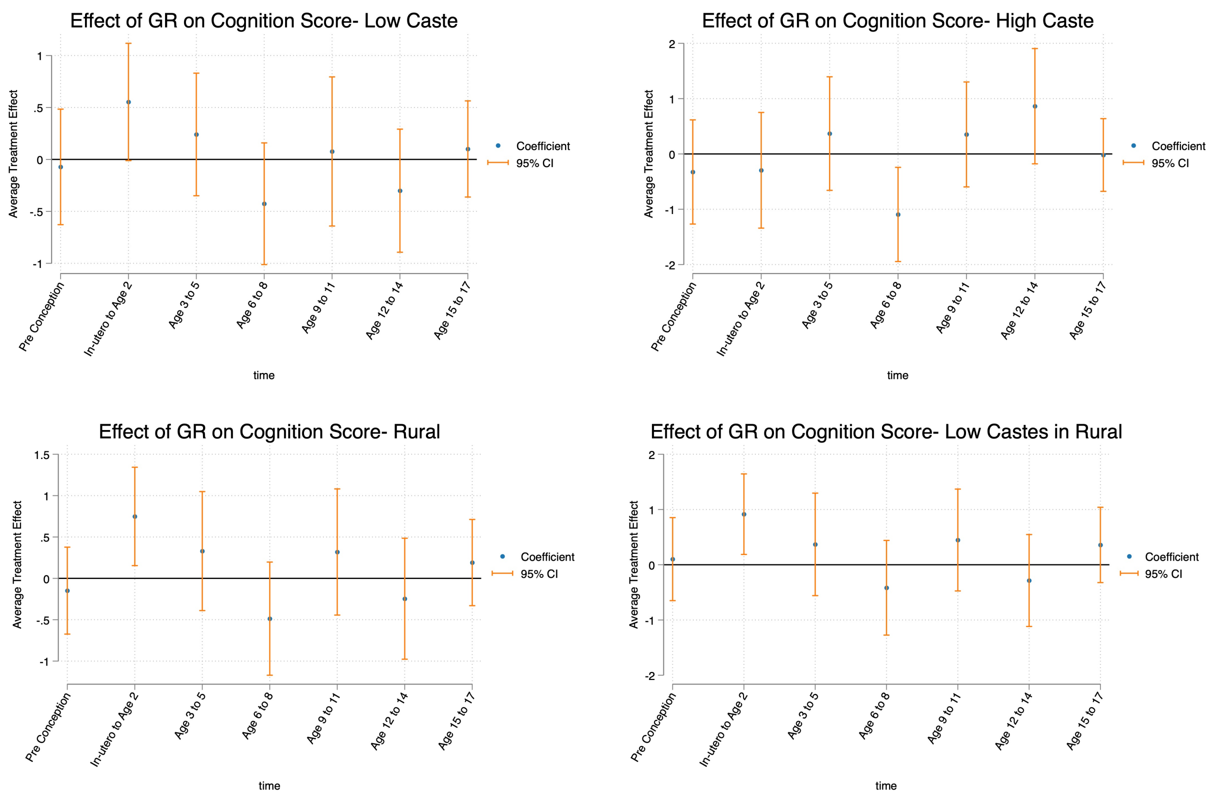
| | Outcome Variable: Cognitive impairment | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Variables | | | | |
| Pre-Conception | 0.017 | 0.016 | 0.049 | 0.015 |
| | [0.064] | [0.066] | [0.077] | [0.101] |
| In-utero to Age 2 | -0.004 | 0.002 | -0.077 | -0.114 |
| | [0.048] | [0.051] | [0.058] | [0.075] |
| | | | | |
| Observations | 15,695 | 15,695 | 15,695 | 15,705 |
| R-squared | 0.054 | 0.067 | 0.068 | 0.079 |
| Birth year FE | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y |
| Mean of Y | 0.063 | 0.063 | 0.063 | 0.063 |
| Controls | | Y | Y | Y |
| State-Birth year Trend | | | Y | |
| State-Birth year FE | | | | Y |

Note: This table shows the effect of early life exposure to the Green Revolution on later life cognitive impairment, a dummy variable equal to 1 if the person has mild cognitive impairment (MCI). The data are Village Dynamics of South Asia (VDSA) merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

# C Heterogeneity

## C.1 Effect on Cognition with Full Age Profile

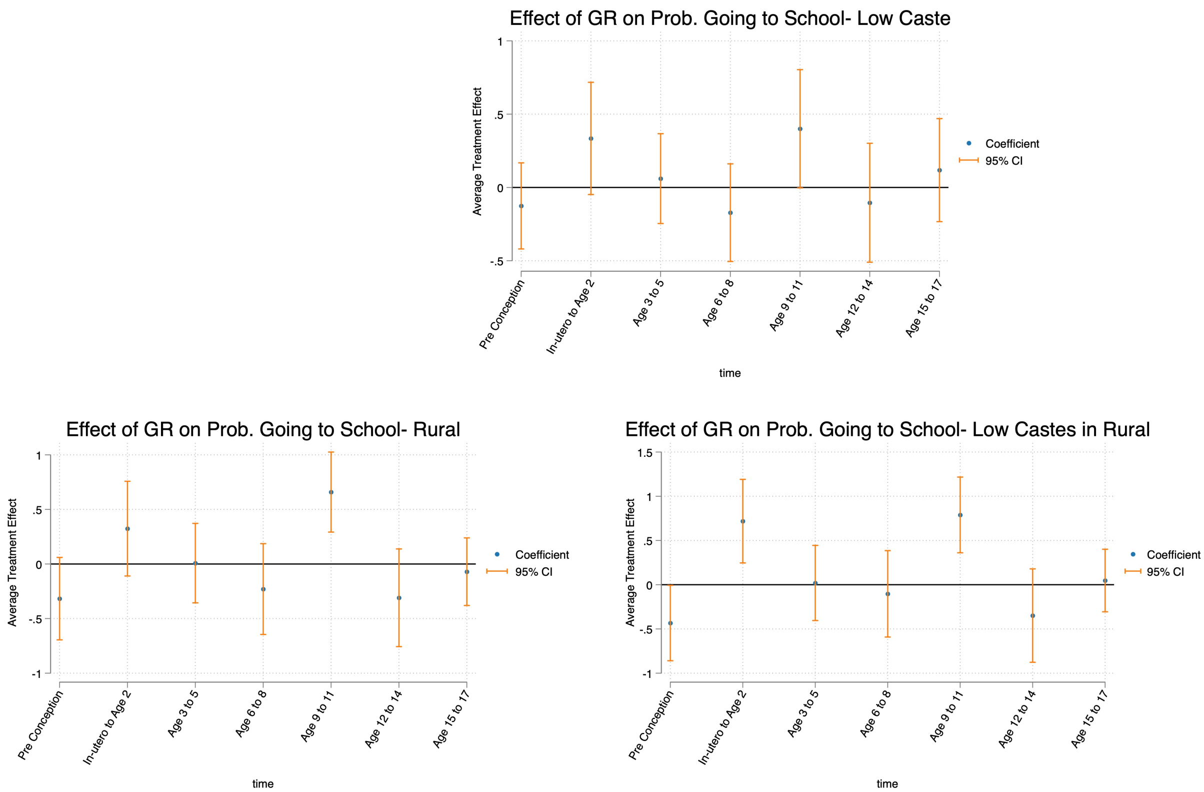
FIGURE 6: Effect on Cognition with Full Age Profile




Note: This figure shows the effect of the Green Revolution at different age groups on the Cognition score for different groups. The coefficients and the 95% confidence intervals are shown.

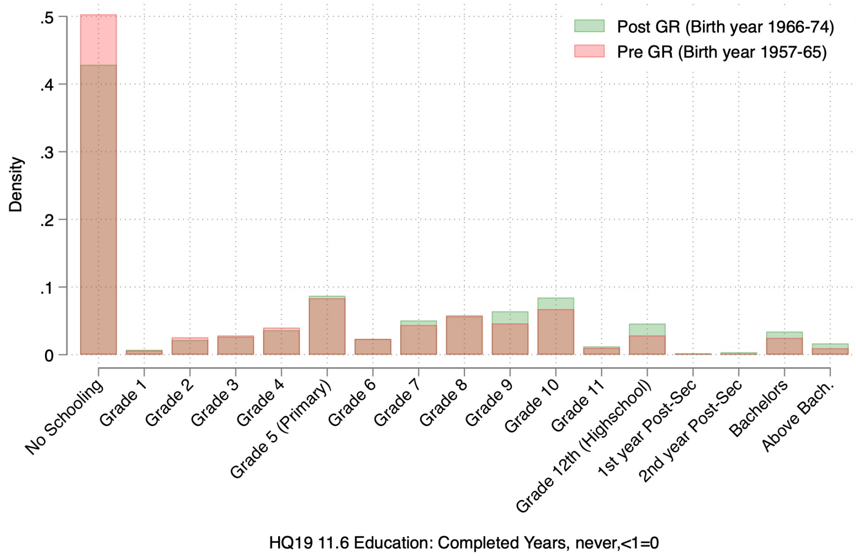
## C.2 Effect on Education

FIGURE 7: Effect on Education with Full Age Profile




Note: This figure shows the effect of the Green Revolution at different age groups on schooling for different groups. The coefficients and the 95% confidence intervals are shown.

FIGURE 8: Distribution of Education Level for Low-Castes from the IHDS data




Note: This figure shows the distribution of the education level for the Low Castes (SC, ST, OBC) for the main sample in our data (born between 1957 and 1974) using another nationally representative data from India, India Human Development Survey (IHDS) using a wave of 2011-12. N=29,191.

## C.3 Results on Any Chronic Condition, Diabetes, and BMI

Panel (B) of Table 2 of our main results shows the effect of early life exposure to the high-yield varieties (HYV) on the total number of chronic conditions, where we do not find a significant effect. We show results in Table 11 to better understand the heterogeneous treatment effects. We use the outcome as whether an individual ever had at least one condition out of blood pressure, diabetes, cancer, lung disease, psych problems, arthritis, stroke, or heart problems. Columns 1 and 5 show that early life exposure to the Green Revolution increases the probability of any chronic condition for men and people living in urban areas. Similarly, in Table 12 Column1, it shows that early life exposure to the Green Revolution increases the probability of ever having diabetes for men. These conclusions are consistent with the recent literature (Sekhri and Shastry, 2024). We also provide evidence of the effect of the Green Revolution on BMI. One potential way to increase the likelihood of chronic conditions might be through dietary changes in early life through a high-fat, high-calorie, and lower-protein diet, which may also translate to higher BMI or obesity later in life.[51] We show these results in Table 13, which shows that the effects on BMI are not

[51] Various studies have documented such relation (Portella *et al.*, 2012, Sekhri and Shastry, 2024).

statistically significant. We are working on including the measures of overweight and obesity, which could be better measurements than BMI, to understand the potential channels for the adverse effects on chronic conditions.

TABLE 11: Effect of Early Life Exposure to the HYV on Chronic Conditions

| | Outcome Variable: Any Chronic Conditions | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Caste |
| Pre-conception | 0.052 | 0.464** | 0.118 | 0.292 | 0.291 | 0.242 |
| | [0.243] | [0.214] | [0.232] | [0.267] | [0.224] | [0.261] |
| In-utero to Age 2 | 0.526** | -0.103 | 0.124 | 0.442* | -0.024 | -0.058 |
| | [0.255] | [0.185] | [0.189] | [0.265] | [0.225] | [0.272] |
| Observations | 6,582 | 9,144 | 11,363 | 7,676 | 8,040 | 5,827 |
| R-squared | 0.126 | 0.108 | 0.101 | 0.127 | 0.123 | 0.147s |
| Birth year FE | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.269 | 0.354 | 0.286 | 0.283 | 0.334 | 0.314 |

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent has any chronic condition. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). The outcome variable takes the value 1 if the respondent reported having any chronic condition and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

# D Robustness

TABLE 12: Effect of early life exposure to the HYV on Diabetes

| | Outcome Variable: Ever had Diabetes | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Caste |
| Pre-conception | 0.033 | 0.075 | 0.127 | 0.132 | -0.013 | 0.026 |
| | [0.111] | [0.122] | [0.090] | [0.134] | [0.121] | [0.115] |
| In-utero to Age 2 | 0.298* | -0.206 | 0.106 | 0.183 | -0.063 | 0.051 |
| | [0.168] | [0.131] | [0.113] | [0.157] | [0.121] | [0.111] |
| Observations | 6,556 | 9,114 | 11,333 | 7,643 | 8,017 | 5,812 |
| R-squared | 0.113 | 0.094 | 0.089 | 0.098 | 0.107 | 0.129 |
| Birth year FE | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y |
| Mean of Y | 0.081 | 0.076 | 0.072 | 0.083 | 0.074 | 0.065 |

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent ever had diabetes. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). The outcome variable takes the value of 1 if the respondent reported ever having diabetes and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 13: Effect of early life exposure to the HYV on Body Mass Index (BMI)

| | Outcome Variable: BMI | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Sample | Men | Women | Low Castes | Urban | Rural | Rural Low Caste |
| Pre-conception | 3.304 | -0.765 | 1.319 | 4.901*** | -0.913 | -3.343 |
| | [2.118] | [2.642] | [1.923] | [1.853] | [2.491] | [3.544] |
| In-utero to Age 2 | -0.118 | 0.701 | 0.733 | -0.636 | 1.162 | 2.228 |
| | [2.570] | [2.094] | [1.657] | [2.230] | [2.271] | [2.385] |
| Observations | 5,883 | 8,328 | 10,382 | 6,865 | 7,334 | 5,362 |
| R-squared | 0.217 | 0.218 | 0.195 | 0.250 | 0.196 | 0.213 |
| Birth year FE | Y | Y | Y | Y | Y | Y |
| Birth District FE | Y | Y | Y | Y | Y | Y |
| Controls | Y | Y | Y | Y | Y | Y |
| State-Birth year FE | Y | Y | Y | Y | Y | Y |
| Weights | Y | Y | Y | Y | Y | Y |
| Mean of Y | 22.63 | 23.72 | 22.68 | 22.99 | 23.20 | 22.84 |

Note: This table shows the effect of early life exposure to the Green Revolution on BMI. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

TABLE 14: Effect of early life exposure to the HYV on Cognition and Chronic Conditions (dropping bottom 5 percentile sample)

| | (1) | (2) |
|---|---|---|
| VARIABLES | Cognition Score | Total Chronic Conditions |
| Pre-conception | 0.15842 | 0.32587 |
| | [0.25740] | [0.28862] |
| In-utero to Age 2 | 0.27438 | 0.12921 |
| | [0.23345] | [0.30354] |
| Observations | 13,579 | 13,580 |
| R-squared | 0.35060 | 0.10104 |
| Birth year FE | Y | Y |
| Birth District FE | Y | Y |
| Controls | Y | Y |
| State-Birth year FE | Y | Y |
| Weights | Y | Y |
| Mean of Y | 0.523 | 0.401 |

Note: This table shows the effect of early life exposure to the Green Revolution on cognition score and the number of chronic conditions. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018 ) of the Longitudinal Aging Study in India (LASI). In this table, we restrict the analysis to the respondents in the top 95 percentile distribution of the height distribution. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.