From Blessing To Burden: The Long-Run Effects of India's Green Revolution

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Abstract

India continues to face a high burden of chronic diseases alongside persistent malnutrition, with the underlying causes still not fully understood. This study explores the unanticipated contribution of Green Revolution technologies, specifically high-yielding varieties of rice and wheat in 1966, to long-term health outcomes. Utilizing regional variation in climatic suitability of wheat and rice, I show that districts with higher Green Revolution adoption have lower crop diversity, reduced lentil and millets production, and lower protein and micronutrients availability. Individuals exposed to the Green Revolution in early childhood tend to be shorter, exhibit higher rates of metabolic syndrome, and have deficits in motor function. I conclude that early childhood adverse nutritional changes can reduce the long-term health benefits of concurrent positive income shocks.

1. Introduction

Despite significant economic growth in recent decades, malnutrition remains a persistent challenge in India, with 56% of the population unable to afford a nutritious diet (FAO, 2024).[1] Simultaneously, India is facing a surge in chronic non-communicable diseases, including cardiovascular conditions, diabetes, neurological disorders (Siddique et al., 2021; Meenakshi, 2016; Pingali et al., 2017; Thow et al., 2016). Qualitative studies suggest that nutritional changes are raising the risk of chronic diseases, though empirical evidence on the onset and drivers of these shifts remains limited (Shankar et al., 2017; Popkin et al., 2001; Shetty, 2002; Shetty et al., 2023; Fareed et al., 2013; Guan et al., 2016).

One hypothesis for these health challenges stems from the agricultural advancements of the 1960s. The advancements focused on caloric sufficiency by enhancing the production of energy-rich crops like rice and wheat, overlooking the importance of nutritional adequacy (Pinstrup-Andersen and Hazell, 1985). This focus led to the Green Revolution in low-income countries like India. From 1965 to 1990, India experienced a significant agricultural transformation characterized by the adoption of high-yielding varieties (HYVs) and extensive agrochemical use, resulting in increased productivity and improved food security (Evenson and Gollin, 2003; Pingali, 2012). However, while this movement effectively reduced caloric undernutrition, experts increasingly argue that prioritizing rice and wheat may have ignored the necessity for diverse nutrient sources like lentils and millets, potentially contributing to health issues associated with dietary shifts (Shiva, 1991; Pingali et al., 2017, 2019). Unlike other neighboring countries, India's predominantly plant-based diet heightens vulnerability to shifts in crop production, as plant foods provide the majority of calories and nutrients (Hopper, 1999).[2] Additionally, historical evidence suggests that interstate agricultural trade restrictions and low market integration within India link regional crop production basket to local consumption patterns (Panikar, 1980; Dasgupta, 1983; Chand, 1999; Chatterjee and Kapur, 2017). Thus, shifts in crop production can directly affect nutrient availability, influencing health outcomes. Despite these anecdotal accounts, empirical evidence on the Green Revolution's long-term health impacts is limited, and analyzing these effects is complicated by insufficient data on individuals born before and after its implementation.

In this paper, I address this gap by answering three key questions: How did the adoption of Green Revolution technologies affect crop diversity, particularly the production of nutrient-rich crops like lentils and millets? Did the increased caloric availability brought by these technologies come at the expense of other critical nutrients, such as proteins and micronutrients? Finally, what are the long-term health consequences for individuals who were exposed to the Green Revolution during early childhood, particularly with respect to growth, metabolic health, cognitive and motor function?

To address the first two questions, I use a longitudinal district-level dataset spanning 270 districts (covering 80% of India's districts at the time) from 1957 to 2007. This dataset provides detailed

[1] Despite India's economic growth exceeding 6 percent annually between 1992 and 2005, stunting declined by only 0.6 percentage points per year, unlike in Western countries where growth significantly boosted average height (Tarozzi, 2008; Floud et al., 2011).

[2] For instance, according to the National Consumption Survey (1991), the wealthiest in India consume up to 14 grams of meat and over 400 grams of milk per day, yet they still rely on plant sources for 60% of their protein intake. Among lower-income groups, who consume as little as 1 gram of meat and under 10 grams of milk daily, up to 96% of protein comes from plants.

information on agricultural production, including the area under HYV of wheat and rice, total cropped area, and production data for 21 major and minor crops, along with fertilizer use and socio-economic variables. For health outcomes, I use individual-level data from the 2017 Longitudinal Aging Study in India (LASI), which includes district and year of birth, along with detailed measures of physical health, metabolic health, cognitive function, and motor skills. This allows me to examine the effects of early childhood exposure to the Green Revolution in an individual's birth district on long-term health outcomes.

I employ a difference-in-differences (DiD) framework to establish causality, leveraging two key variations: the timing of the Green Revolution's introduction in 1966 and cross-district differences in potential productivity gains for wheat and rice based on climatic conditions. The underlying logic is that favorable climatic conditions for wheat and rice production significantly influence the uptake of Green Revolution technologies. Regions with higher potential productivity gains from HYVs are more likely to transition from traditional varieties to these modern technologies.

To quantify potential productivity gains, I use models developed by the Food and Agriculture Organization (FAO), which estimate the maximum potential crop yields for wheat and rice at a high-resolution grid cell level. These models assess climatic suitability and categorize yield estimates along two key dimensions: (i) input levels—high or low—and (ii) irrigation conditions—irrigated or rainfed. Specifically, potential yields under low input and rainfed conditions represent the output from traditional varieties, while those under high input and irrigated conditions reflect the potential yields achievable through the adoption of HYVs. I first aggregate these yield estimates to the district level and then calculate the difference between the two measures to create a metric of potential productivity gains of wheat and rice (Nunn and Qian, 2011; Bustos et al., 2016; Bartik et al., 2019; Moscona, 2023).

To explore this, I convert crop production data into caloric and nutrient equivalents using the National Food Composition Table (2017). Employing the same difference-in-differences design, I assess the impact of potential productivity gains on both calorie availability and nutrient supply per calorie. The analysis reveals that exposure to higher potential productivity gains boosts calorie production by 20% and increases carbohydrate supply per calorie by 0.6%. Conversely, protein supply per calorie declines by 3%, while iron, folate, and zinc decrease by 2%, 9%, and 2%, respectively.[3]

After establishing the changes in caloric and nutrient availability, I examine how these nutritional shifts affect health outcomes. Using difference-in-differences and cohort event-study models, I analyze whether cohorts born just before and after the Green Revolution introduction in 1966 show persistent differences in health outcomes. By comparing individuals born in different levels of potential productivity gains shortly before the Green Revolution with those born shortly after, my design isolates the specific effect of early childhood exposure to the Green Revolution compared to exposure at slightly older ages. The focus on early life is based on evidence of fetal origins of adult outcomes (Barker, 1994; Almond et al., 2018). Diets high in calories but low in protein and micronutrients may not cause visible deficiencies. However, multiple mild deficiencies combined with excess energy can lead to physiological changes and disrupt metabolism. This disruption is particularly harmful during in utero and early childhood, leading to stunted growth, metabolic disorders, and impaired development.

[3] Plant foods contribute around 94% of total food energy, micronutrients and 85% of total protein (Hopper, 1999)

(Stocker et al., 2005; Hoppe et al., 2004; Mehta et al., 2002; Stein et al., 2003; Christian and Stewart, 2010; Zou et al., 2021; Rees, 2019). [4]

I estimate the effects of Green Revolution exposure on adult height, metabolic syndrome, cognitive decline, and motor skill deficits. My results show that Green Revolution exposure significantly reduces height and increases metabolic syndrome incidence. Specifically, a one standard deviation increase in productivity gains results in a 0.4 cm decrease in height, notable since average heights in India grew by only 4 cm in the 20th century (NCD-RisC, 2016). Additionally, this increase leads to a 0.025 standard deviation rise in metabolic syndrome, driven by a 3.6 percentage point increase in hypertension and a 1.2 percentage point rise in diabetes. While I observe a rise in cognitive imbalance and motor function deficits, these effects are not statistically significant.

I also explore alternative mechanisms and find they are unlikely to explain the observed effect on health outcomes. The results are robust to controlling for baseline characteristics, including urbanization, literacy, service sector employment, and healthcare access, each interacted with a linear time trend as proxies for sedentary lifestyles, processed food consumption and access to healthcare. Another concern is that the Green Revolution may have influenced long-term health through non-nutrition- related factors, such as increased agrochemical exposure. I provide suggestive evidence that this channel is not significantly influencing the results in three ways. First, I include fertilizer exposure at birth-district and birth-year level in my preferred specifications. Even after controlling for fertilizers, pesticide exposure remains a concern due to adoption practices, with rural populations likely more exposed to pesticides. Second, I compare rural and urban births to examine the impact of these factors on health outcomes, finding that height reduction is smaller in rural areas. This suggests that pesticide exposure may not be the main factor. Additionally, there are no significant differences in metabolic syndrome, cognitive imbalance, or motor deficits between rural and urban births. Lastly, I create an indicator for the sowing months, which are also the peak months for fertilizer and pesticide application, and perform a heterogeneity analysis to assess whether individuals born during these months exhibit different outcomes. I do not find any significant differences in the results. I also rule out the influence of adult health behaviors, such as smoking, alcohol consumption, and exercise, spillover effects as well as composition effects that might have occurred if the Green Revolution affected the survival and health outcomes of specific groups of individuals.

Due to the unavailability of individual-level dietary data from the study period, I provide indirect evidence linking consumption patterns to negative health outcomes. First, I show that individuals born after the Green Revolution in districts with higher productivity gains live in households that consume more rice per capita, purchased through ration shops. Additionally, hypertension and diabetes are more prevalent in households with higher cereal expenditures and less common in those with higher spending on animal-based foods. Finally, by comparing men born before and after the Green Revolution in high productivity gain districts, I find suggestive evidence that those born later tend to consume fewer

[4] One theory suggests that undernutrition in utero can lead to a "thrifty phenotype," which helps the fetus optimize calorie use but increases the risk of metabolic syndrome later on, particularly in calorie surplus environments later in life. While this adaptation is linked to nutritionally scarce environments during fetal development, it may not explain the health outcomes of those born after the Green Revolution, when caloric supply improved but the quality of nutrition may have been diminshed (Sekhri and Shastry, 2024).

micronutrients than recommended.

My study on the Green Revolution of 1960s in India sheds light on its long-term, unintended health impacts, connecting its historical context to the current discourse on Green Revolution 2.0. This contemporary approach emphasizes sustainable agricultural practices aligned with the Sustainable Development Goals, particularly zero hunger and responsible consumption and production. My research shows that Green Revolution technologies reduced crop diversity, especially affecting lentil and millet production. While caloric availability increased, access to protein and micronutrients declined. Additionally, I find that individuals exposed to the Green Revolution in early childhood face challenges such as shorter stature, higher rates of metabolic syndrome, and deficits in motor function. These findings emphasize the importance of enhancing crop diversity and nutrition while promoting responsible agricultural practices to improve health outcomes in the future.

This paper makes three primary contributions. First, it complements recent scholarship on the effects of the Green Revolution (Gollin et al., 2021; Moscona, 2023; Foster and Rosenzweig, 1996). Prior research estimating the health impacts of the Green Revolution has typically focused on contemporaneous changes in infant health. For instance, Bharadwaj et al. (2020) and Von Der Goltz et al. (2020) find declines in infant mortality, while Brainerd and Menon (2014) reports a positive association between increased fertilizer use and higher infant and neonatal mortality. In a correlational study in Bangladesh, Headey and Hoddinott (2016) shows that while child weight-for-height improved due to the Green Revolution, height-for-age did not, suggesting a complex interaction between agricultural practices and nutrition. Most relevant to this study, Sekhri and Shastry (2024) who investigate the long-term effects of Green Revolution exposure on diabetes in India, using historical aquifer presence as an exogenous source of variation for HYV adoption. Their findings show increased diabetes risk in cohorts born after the Green Revolution, especially in regions with more aquifers. I provide new evidence on the decline in crop diversity and nutrient-rich crops, highlighting the long-term effects on nutrient availability— particularly reductions in protein, iron, zinc, and folate which associates with adverse health outcomes.

Second, my paper contributes to the broader literature on how economic and nutritional resources during in-utero and childhood affect adulthood health and economic outcomes. Numerous studies document the impacts of early experiences on health status, educational attainment, test scores, wages, and mortality rates (see (Currie and Vogl, 2013; Almond and Currie, 2011; Almond et al., 2018)). A significant body of research highlights the long-term benefits of improved early childhood nutrition in developing nations (Adhvaryu et al., 2019, 2020; Field et al., 2009; Clay et al., 2019; Shah and Steinberg, 2017; Almond and Mazumder, 2011; Hoynes et al., 2016). This paper specifically shows that exposure to a diet low in protein and micronutrients during early childhood can lead to long-term health consequences, even when caloric intake is sufficient.

Third, my paper introduces a new resource for studying long-term outcomes in the Indian context: the Longetudinal Ageing Survey of India. Previous work focusing on long-run implications of early-life interventions in India has been typically challenged by the fact that there is lack of publicly available datasets containing detailed information on birth location linked to long-run outcomes. In contrast, LASI contains precise information on both location and date off birth along with detailed health outcomes.

The rest of the paper proceeds as follows: Section 2 presents the background on the Green Revolution in India and the underlying theory of change in nutrition and health outcomes. Section 3 describes the data, while Section 4 details the empirical strategy. Section 6 discusses the results and Section 7 discusses alternative mechanisms. Section 8 concludes.

2. Background

2.1 Green Revolution in India

The Green Revolution in India, which began in the 1960s, marked a transformative shift in agricultural productivity. This transformation was driven by substantial investments from international organizations, such as the Rockefeller Foundation and the Ford Foundation, aimed at addressing global food insecurity and low agricultural productivity (Saha, 2013).

Several institutional changes during the 1960s accelerated this process. Prior to this period, there was minimal intellectual property protection for crop varieties, but the introduction of Plant Breeders' Rights provided incentives for private sector investment in crop breeding. International agricultural research centers (IARCs), supported by global donors, were established, including the International Rice Research Institute (IRRI) and the International Centre for Maize and Wheat Improvement (CIMMYT), which eventually coalesced into the Consultative Group for International Agricultural Research (CGIAR). This combination of public and private sector initiatives spurred a rapid increase in the development of high-yielding crop varieties (Evenson and Gollin, 2003).

A pivotal moment in this period was the early 1960s, when high-yielding varieties (HYVs) of wheat and rice were developed. The first breakthrough came with the release of IR8 rice, or "miracle rice," at IRRI in 1966. IR8 could yield up to 5 tons per hectare and matured 30-40 days faster than existing varieties (De Datta, 1978). Similarly, the development of semi-dwarf wheat varieties, based on Japanese strains like Norin 10, was instrumental in increasing wheat productivity. These semi-dwarf varieties, refined at CIMMYT in Mexico during the 1950s, were introduced to India in the mid-1960s (Dalrymple, 1979). Technological advancements primarily focused on rice and wheat, which were more successful in raising productivity than other crops. Yield increases from HYV in crops like sorghum and millet were smaller, as scientists had already built a critical mass of knowledge around rice and wheat, which did not exist for other crops (Gollin et al., 2021; Estudillo and Otsuka, 2013)

Indian scientists first tested these wheat and rice varieties in 1962 and 1964, respectively, and by the 1965–1966 crop year, they were rolled out across the country. This was supported by a broader "high-yielding variety technology (HYVT)" package, which included chemical fertilizers, pesticides, controlled irrigation, and mechanization. These technologies significantly increased crop yields, with 62% of cereal production coming from HYVs by 1975, boosting India's agricultural output (Barker et al., 2014). Between the mid-1960s and late 1970s, wheat production tripled, and rice yields surged. This rise in productivity helped India achieve food self-sufficiency.

The success of the Green Revolution varied widely across India. The northwestern states of Punjab, Haryana, and Western Uttar Pradesh benefited greatly due to their favorable climatic conditions and better infrastructure. However, other regions, like eastern India, did not see the same level of success. Issues like limited irrigation, poor infrastructure and differences in adaptability local conditions like diseases, pests, and abiotic stress made it difficult for these areas to adopt Green Revolution practices. For example, the use of HYV rice in North India rose from 11% in 1965-69 to 82% in 1975–79. In contrast, in rain-fed states like West Bengal, Bihar, and Orissa, HYV adoption averaged only about 25% during the same period (Barker et al., 2014; Gollin et al., 2021).

2.2 Potential Dietary Effects of Adoption of HYV Wheat and Rice

The favorable adoption of HYV wheat and rice in certain regions has the potential to affect diets through several interrelated channels, including income effects, shifts in crop diversity, and changes in relative prices.

First, HYV adoption in districts with favorable climatic conditions and infrastructure led to increased agricultural productivity, which in turn raised farm incomes (Foster and Rosenzweig, 1996). Higher incomes could increase demand for more diverse and nutritious diets, potentially enhancing dietary diversification and improving both calorie and nutrient intake. However, this outcome hinges on the availability of diverse food groups. Supply constraints stemming from limited technological advancements and insufficient market support for nutrient-rich crops like millets and lentils may hinder their availability, even as demand for diverse diets increases. This might restricts households' ability to convert income gains into enhanced dietary quality. (Pretty and Bharucha, 2014; Pingali, 2019; Pingali et al., 2017).[5] Additionally, if wheat and rice are considered normal goods, an increase in income would likely boost their consumption, which may not necessarily contribute to improved dietary diversity.[6] Higher income might also not necessarily translate into increased spending on more diverse foods, as households may allocate additional resources to non-food expenditures while keeping consumption centered on readily available wheat and rice.

In addition to income effects, HYV adoption can significantly influence diets by reshaping agricultural production patterns. One theory is that the HYV adoption in agro-climatically suitable places likely promoted the cultivation wheat and rice at the expense of crop diversity, which could reduce access to nutrient-dense options such as pulses and millets. While wheat and rice provide essential calories, they are relatively low in protein compared to other crops. Wheat contains about 12-15% protein, and rice provides around 7-8%; both grains fall short compared to pulses, which offer 20-25% protein. Additionally, while rice has a higher amino acid content than wheat, both grains are inferior to pulses in this regard, with pulses supplying 45 mg of essential amino acids per gram compared to rice's 16.5 mg and wheat's 9.5 mg. Furthermore, the emphasis on wheat and rice may result in reduced availability of essential micronutrients, as millets and pulses are often richer in vital nutrients like iron,

[5] Appendix Figure A.10 shows the per capita availability net of exports and import for rice, wheat, pulses, and coarse cereals in India from 1956-2007. While wheat and rice availability has increased, pulses and coarse cereals have declined.

[6] There was a class division in food in India as well beofre Green Revolution: the rich ate 'fine' cereals—rice and wheat—and the poor ate 'coarse' cereals (Umanath et al., 2018). Increase in the supply and lower prices of "rich" people food could also have led to a shift in consumption patterns. (https://www.nationalheraldindia.com/india/why-do-the-rich-want-the-poor-mans-food)

calcium, folate, and zinc. This shift may lead to lower nutrient availability despite increased caloric availability.

The decline in crop diversity may also have implications for relative prices. There were both formal and informal restrictions on the movement, stocking, and trading of agricultural produce. These barriers lead to a slower flow of goods from surplus to deficit markets, hinder market integration, and result in price dispersion of different crops across districts. With the decline in the the production of nutrient-rich crops due to HYV adoption, their prices might have increased in regions with higher production of wheat and rice, limiting affordability and accessibility. [7] At the same time, the cheaper cost of wheat and rice might influence diet towards more consumption of these energy-dense foods. Consequently, households may become increasingly dependent on a narrower range of nutrient-poor crops, which could undermine long-term nutritional outcomes. However, lower prices for wheat and rice can theoretically free up household income to purchase a wider variety of foods, potentially improving dietary diversity and nutritional quality.

Add something on why people might have shifted to wheat/rice -going from millet bread to wheat bread. Rice and wheat

Hopper (1999) highlights that India's diet has long relied on plant-based foods, with pulses providing essential protein and amino acids. However, between 1960 and 1995, pulse consumption fell from 63 to 36 grams per day, leading to a loss of 634 mg of amino acids daily. Rising costs likely drove this decline, particularly affecting lower-income groups. The shift to a diet dominated by rice and wheat, with lower protein quality, may have worsened nutritional outcomes, contributing to lower physical growth. For instance, Indian males, by age 18, average 164 cm tall, which is 96% of the height of Chinese males and 91% of American males.

2.3 Prior Evidence on Health Effects of In-Utero Nutritional Exposure

Nutritional Exposure

Inadequate nutrition during early life can disrupt the body's development, leading to long-lasting negative health effects. Poor maternal nutrition is closely linked to low birth weight and can also affect adult height and growth. In the field of nutrition, the concept of "developmental origins of adult disease" emerged from mid-1980s epidemiological research in the United Kingdom by Barker (1994). His studies highlighted significant correlations between maternal undernutrition, low birth weight, and an increased long-term risk of metabolic syndrome. These early nutritional deficits can cause epigenetic and physiological changes, programming the body to conserve energy and store fat in response to nutrient scarcity. This adaptation, called the *"thrifty phenotype"*, alters metabolic functioning to prepare for a life of limited food availability. However, in situations where food becomes abundant later in life, this adaptation can increase the risk of metabolic disorders, such as cardiovascular health. While the thrifty phenotype could explain outcomes in nutrient-deprived settings, it seems less likely

[7] From 1972-73 to 2011-12, annual per capita sorghum consumption dropped from 8.5 kg to 1.58 kg in urban areas and from 19.2 kg to 2.42 kg in rural areas. Pearl millet intake also fell sharply, from 11.5 kg to 0.97 kg in rural areas and from 4 kg to 2.82 kg in urban areas. (Rao et al., 2010; Basavaraj et al., 2010).

to apply to populations born after the Green Revolution, where caloric supply significantly improved (Sekhri and Shastry, 2024).

A more likely explanation for health issues in post-Green Revolution cohorts is the poor "quality" of nutrition, particularly the imbalance of protein. Observational and experimental studies on animals and humans indicate that insufficient protein intake during pregnancy can lead to long-term health effects, including impaired cognitive and motor development, lower height, and an increased risk of conditions like obesity, hypertension, glucose intolerance and type II diabetes (Samuelsson et al. 2008; Stocker et al. 2005). Even though caloric supply increased after the Green Revolution, many diets may have remained imbalanced, heavily reliant on carbohydrates, and deficient in essential proteins.

Micronutrient deficiencies are another potential pathway through which early-life nutrition shapes long-term health. Experimental studies on mother-child dyad and animals have shown that a lack of folate, zinc, iron and calcium, during critical periods can have epigenetic effects that predispose individuals to chronic conditions, lower linear growth and cognitive issues (Waterland et al. 2010; Dominguez-Salas et al. 2013). Micronutrient deficiencies have also been linked to stunting and wasting and leading to poorer health, lower educational attainment and decreased work capacity and earning potential (Bailey et al., 2015). Moreover, maternal micronutrient deficiencies, such as low iron and folate intake during pregnancy, have been associated with impaired cognitive development and lower IQ scores in children (Gernand et al., 2016) and increased risk of neuropsychiatric disorders in the long-run (Martorell, 2017). In conclusion, the long-term impact of the Green Revolution on adult health is uncertain. While an increase in caloric availability during gestation and early childhood would be expected to improve health, this benefit may be undermined by a decline in nutritional quality—specifically, lower intake of protein and micronutrients. My findings on adult health outcomes are consistent with this quantity-quality tradeoff.

3. Data

My analysis examines the relationship between potential productivity gains, crop diversity, production, nutrition and health. Below, I describe the data and the measurement of each variable.

3.1 Adoption of HYV and Crop Diversity

Indian Agricultural and Climate Data (IACD) and International Crops Research Institute for the Semi-Arid Tropics–District Level Data (ICRISAT):

To understand the effect on crop diversity and production of different crops, I needed information regarding area and production of crop pre and post Green Revolution introduction. These two sources provide district-level annual data on the area planted to HYV for wheat and rice, total area cropped under each crop (in hectares), production and yield (in 000 kgs per hecatre) for 5 major and 19 minor crops which constitute 95% of agricultural production in India. The data spans 266 districts (80% of all districts) in India from 1957 to 2007. Apart from the data on agricultural outcomes, the dataset also has information on socioeconomic and agro-ecological variables. The 13 states covered in the dataset (as per 1961 census) are Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal. Figures 1 and 2 illustrate that HYV wheat and rice adoption reached 90% by the 1990s, with significant yield increases following the Green Revolution.

I compute share of HYV wheat and rice adoption - I sum the area planted to HYV wheat and rice for each district and year. Then, I divide the sum by the total area cultivated in each district and year. For crop diversity index, I create Shannon Diversity Index. Shannon Diversity Index is measured as $\sum_{i=1}^{n} p_i \, ln(\frac{1}{p_i})$, where p_i is the area planted under crop i in year t. The range of Shannon Index is $[0, ln(n)]$. In my dataset, the range is [0.06, 2.55].[8] Appendix Figures **??** and 4 show the average district-level HYV adoption and crop diversity between the time period 1960-2007.

For analysis on nutrient availability, I calculate the caloric and nutrient equivalents of each crop by multiplying production values by their caloric and nutrient content from the National Food Composition Table (2017).

3.2 Potential Yield of Wheat and Rice

Food and Agro-Economic Zones (FAO-GAEZ) Data

The second key measure in my analysis for understanding Green Revolution exposure is the potential productivity gains of wheat and rice. I develop this metric based on the idea that districts with higher potential gains are more likely to adopt Green Revolution technologies. This metric is derived from theoretical models of maximum potential crop yields provided by the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO GAEZ). These models, constructed using parameters from controlled experiments rather than data on actual agricultural inputs and outputs, estimate yield potentials by considering factors such as temperature, radiation, and moisture in specific grid cells. The model incorporates key crop characteristics, including the growth cycle duration (from emergence to maturity), yield formation period, maximum rate of photosynthesis at current temperatures, leaf area index during peak growth, harvest index, crop adaptability, sensitivity of growth cycle length to heat, crop water needs at different development stages, and yield response to water stress (FAO GAEZ).

The FAO reports this data in a 9.25 km x 9.25 km raster grid, with each cell containing maximum potential yields for specific crops in that area. The data is available at "low" and "high" input levels, and, "rainfed" and "irrigated" conditions. Under low-input, traditional farming systems is assumed. It relies on traditional varieties, labor-intensive methods, with no use of fertilizers, pesticides, or conservation measures. In high-input systems, farming is assumed to be market-oriented. It uses high-yielding varieties, is fully mechanized where possible, requires minimal labor, and applies optimal amounts of fertilizers and chemicals for pest, disease, and weed control (FAO GAEZ). I aggregate the grid cell-level data to calculate the average potential yield for rice and wheat under both low-input, rainfed conditions and high-input, irrigated conditions for each district. The potential productivity gains metric is then calculated as the difference between the potential yields of wheat and rice under

[8] I also compute alternative measures for robustness checks: Simpson Diversity Index, which is measured as $1-\sum_{i=1}^{n} p_i^2$ and number of crops.

high-input, irrigated conditions and low-input, rainfed conditions.[9] The district-level aggregated measures of potential yield for wheat and rice under (low input, rainfed) and (high input, irrigated) are shown in Figures A.3-A.6.[10, 11]

3.3 Individual Health Outcomes

Longetudinal Ageing Survey of India (LASI, 2017-18)

To analyze health outcomes, I need data on individuals' district of birth, year of birth, and health outcomes for those born before and after the Green Revolution. The LASI survey, a nationally representative dataset of individuals aged 45 and older (and their spouses, including those under 45), provides such information. It includes 42,000 individuals born between 1945 and 1985 from 13 states, sampled from 2,440 villages and towns based on the 2011 census. The dataset covers demographics, household economic status, chronic and symptom-based health conditions, functional and mental health, biomarkers, employment, life satisfaction, childhood health, and family medical history. Crucially, it contains data on "district of birth". I match LASI data with IACD data based on district of birth rather than residence. This process provides individual-level health outcomes for people born in 251 districts.[12,13]

I use the following responses from LASI: (i) Height measured in cms, (ii) self-reported incidence of hypertension, diabetes, chronic heart disease, high cholestrol, (iii) self reported (diagnosed) neurological or psychiatric problems including Alzheimer's, Parkinson's, epilepsy, depression, anxiety, schizophrenia, bipolar disorder. I create two measures of obesity: (i) Body Mass Index (BMI) criteria and, (ii) Waist-Hip circumference ratio (WHR).[14] I also create metrics for cognitive functioning and motor balance. I measure cognitive functioning using Mini-Mental State Examination (MMSE) attributes from the LASI data, with two binary variables: (i) poor cognitive functioning (MMSE score $\leq$ 15), where the sample mean is 15, and (ii) mild cognitive impairment (MMSE score $\leq$ 19), the cutoff used in the medical literature. [16] Motor balance is assessed using (i) grip strength deficit, with an

[9]Figures A.1 and A.2 illustrate the FAO's potential yield measures for wheat at the grid cell level.

[10]The FAO identifies two types of rice: dryland rice and wetland rice. Drylands are areas where the aridity index (AI)—the ratio of annual precipitation to mean annual potential evapotranspiration—is no more than 0.65. These are further classified into arid, semi-arid, and dry-subhumid zones. Two Indian states, Rajasthan and Gujarat, have the highest percentage of dryland, with most of their regions falling under arid or semi-arid categories, where dryland farming is the norm. For these states, I focus on the values for dryland rice. Although other states have semi-arid regions, I take a conservative approach, as the Green Revolution was more favorable for wetland agriculture, with HYVs designed for irrigated conditions, requiring agrochemicals and lacking drought resistance. (Aurora, 1991)

[11]Additionally, for robustness, I collect information on the adoption of HYV wheat and rice in South Asia (excluding India) from various sources (Dalrymple, 1986b,a; Evenson and Gollin, 2003). I create a different version of this metric utilizing the time variation from South-Asian adoption rates which is exogenous to the the local conditions in India.

[12]26% of the individuals either migrated to another district or another state.

[13]A drawback of survey data is age heaping, but this issue is less significant in the LASI. The questionnaire collects birth month, year, and age, allowing for correction of any discrepancies. Figure A.7 shows that there is no issue of age heaping in the LASI data.

[14]BMI is calculated as $\frac{Weight(kg)}{(height(m))^2}$. The BMI obesity dummy is equal to 1 if BMI$\geq$30, WHR obesity dummy is equal to 1 if WHR is greater than 0.9 in males or greater than 0.85 in females.[15]

[16]MMSE is a 30-point questionnaire assessing orientation, recall, naming, number series, computation, executive function, and drawing, see Banerjee et al. (2018)

indicator set to 1 if grip strength (measured in kg) is below the age and gender-specific cutoff, and (ii) balance deficit, defined as 1 if an individual's score on a timed walk and tandem balance test is below the cutoff.

To address the numerous outcome variables, I follow the approach by Kling et al. (2007),Hoynes et al. (2016), and Sekhri and Shastry (2024) by constructing summary standardized indices that aggregate information from various outcomes.[17] Specifically I create four indices: metabolic syndrome index (hypertension, diabetes, obesity measures, chronic heart and high cholestrol), cognitive imbalance index (neurological disorder and cognitive metrics), motor deficit index (grip strength and balance deficit). Aggregating measures within a domain, like metabolic syndrome, increases statistical power. The summary index is calculated as the average of standardized z-scores f or each component, where each z-score is the value minus the mean, divided by the standard deviation. Higher index values indicate worse outcomes. Table 1 provides summary statistics for the demographics and health outcomes in the LASI data.

3.4 Household Consumption

National Sample Survey: Consumption Expenditure (1999)

To understand the effect on actual consumption, my analysis utilizes data from the 55th round (1999-2000) cross-sectional survey on consumption expenditure conducted by the National Sample Survey Organization (NSSO). The survey encompasses around 70,000 rural households across 8,000 villages and 45,000 urban households from 4,500 urban blocks within the 13 states under analysis. It captures household expenditures and quantities for each food item consumed in the past 30 days, including home grown foods and gifts, both valued at local prices. There are 169 different food items covered, including 12 rice or wheat products, 9 pulse types, 5 millets and coarse cereals, 7 dairy products, and various vegetables, spices, meat and fish. Caloric and nutritional intake in the household is calculated by multiplying the quantity consumed by the caloric or nutrient content (based on estimates from the India Food Composition Table, 2017, National Institute of Nutrition, India). The surveys also provide and household demographics and characteristics. This data is utilized to assess the effect on nutrition using a metric: nutrition adequacy ratio. This ratio is calculated as the ratio of the actual intake of a nutrient to the recommended intake in a household. I calculate the recommended intake using the Indian Council of Medical Research guidelines for different age groups and sex, considering household composition by age and sex.

3.5 Additional Controls

Data on population density, share of urban population, share of service sector employment, share of literate population in Indian districts comes from 1961 census compiled by Reeve Vanneman at the India District Database. I also include data on district level mean annual precipitation and temperature

[17] Kling et al. (2007) and Hoynes et al. (2016) use the control group mean and standard deviation to calculate the z-score in their randomized experiment and quasi-expiremental design. In my setting, I apply a similar method, using the mean and standard deviation of cohort born before the Green Revolution.

obtained from Matsuura and Willmott (2009). For th healthcare availability, I use the data on number of primary healthcare centres from Iyer (2010).

4. Empirical Strategy

I seek to estimate the effect of potential productivity gains on crop diversity, crop production, nutrient availability, and health outcomes. First, I construct a metric for potential productivity gains in wheat and rice using FAO-GAEZ data. I then link this metric to district-level agricultural and health data to analyze its impact on diversity, production, nutritional availability, and health. In this section, I explain how I construct the potential productivity gains metric and outline the estimating equations.

Potential Productivity Gains

The key insight behind this metric is that agricultural production patterns are influenced by climatic features. Regions with greater climatic suitability for wheat and rice are likely to benefit more from transitioning to HYV from traditional varieties. I measure potential productivity gains by calculating the shift in productivity from low-input, rainfed farming typical of pre-Green Revolution agriculture to high-input, irrigated systems (associated with Green Revolution technologies).

Since wheat and rice are complementary crops—wheat is grown in the Rabi (winter) season and rice in the Kharif (summer/monsoon season)— farmers can cultivate both within the same year. By assessing potential gains for both crops, I capture the overall productivity potential of a district. I create the measure as follows:

$$\begin{aligned}\text{ProdGain\_wr}_d &= \frac{\Delta P_{w,d} + \Delta P_{r,d}}{2} \\ &= \frac{\left(P^h_{w,d} - P^l_{w,d}\right) + \left(P^h_{r,d} - P^l_{r,d}\right)}{2}\end{aligned}$$

where P^h_w and P^h_r are potential productivities at high input level and irrigation for wheat and rice; and, P^l_w and P^l_r are potential productivities at low input level and rainfed condition for wheat and rice in district d.

Estimating Equations

My goal is to estimate the change in outcomes in the post-1966 period relative to pre-1966 period between districts that likely adopted Green Revolution technologies. To do that, my empirical strategy exploits two sources of variation: (i) the time variation in the introduction of Green Revolution in 1966, and (ii) the cross-sectional variation in potential productivity gains. I utilize the follwoing difference-in-differences (DID) model:

$$Y_{d,t} = \theta\ (\text{ProdGain\_wr}_d \times \text{Post}_t^{1965}) + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{d,t} \tag{1}$$

where $Y_{d,t}$ is the outcome of interest. The main outcome variables are (i) share of HYV wheat and rice area, (ii) crop diversity, (iii) area under different crops, (iv) production of different crops, and (v) calorie and nutrient availability per calorie in district d in year. Post_t^{1965} is an indicator for years post 1965, $X_{d,t}$ are either time varying district characteristics: average precipitation and temperature or baseline district characteristics interacted with year fixed effects (described when introduced in the analysis), δ_d and τ_t are district and time fixed effects. Standard errors are clustered at the district level. The coefficient of interest in equation 1 is θ, which is the estimated effect of potential productivity gains on crop diversity, area and production of different crops and nutrient availability. For concreteness, consider the case with crop diversity as the dependent variable. A negative coefficient, $\hat{\theta}$, indicates that crop diversity declined in districts with higher potential gains compared to those with lower gains after the Green Revolution was introduced in 1966.

Equation 1 examines the average effects of the potential productivity gains on the outcomes of interest. I also estimate a fully flexible specification to estimate time varying effect of the Green Revolution that takes the following form:

$$Y_{d,t} = \sum_{t=1957}^{2007} [\gamma_t (Year_t \times \text{ProdGain\_wr}_d)] + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{d,t} \tag{2}$$

where $Y_{d,t}$ is the outcome of interest, $Year_t$ is a set of year dummies, and γ_t represents the coefficients showing the relationship between potential productivity gains and the outcome each year. This approach captures effects that can grow, diminish, or change non-monotonically over time. It also tests the identifying assumption by estimating differential trends before the Green Revolution. The estimated coefficient β_ts show the correlation between potential productivity gains and outcomes in each period. If, for example, the likely adoption of HYV in areas with higher potential productivity gains decreased crop diversity, then the β_ts should be constant before 1966 and negative with increasing magnitude post-1966, reflecting the gradual adoption of HYVs and its growing impact on crop diversity.

Health Outcomes

I estimate a similar model using individual-level data on health outcomes, applying a difference-in-differences approach. This compares the health outcomes of individuals from the same district, who experienced different potential productivity gains from HYV wheat and rice adoption based on their birth year, while controlling for unobserved shocks to health outcomes that may also vary by birth year. Specifically, I estimate the following:

$$Y_{i,d,t} = \theta\ (\text{ProdGain\_wr}_d \times \text{Post}_t^{1965}) + \beta_1' X_{i,d,t}^1 + \beta_2' X_{d,t}^2 + \delta_d + \tau_t + \varepsilon_{i,d,t} \tag{3}$$

where $Y_{i,d,t}$ is the health outcome of interest for the individual, $X_{i,d,t}^1$ are individual level controls for gender, religion, caste and whether the individual was born in rural area, $X_{d,t}^2$ are district level controls including fertilizer exposure, mean rainfall and temperature at the year of birth to isolate the effect from the broader impacts of the early childhood fertilizer exposure and weather, δ_d and τ_t are district and year of birth fixed effects. The standard errors are clustered at the district of birth level.[18]

The identification strategy in equation 3 differs from many previous design-based studies in the fetal origins literature. Typically, natural experiments like famines or disease outbreaks are short-term—they occur and then end. However, exposure to the Green Revolution is continuous. Once the Green Revolution technologies are introduced in a district, they remain in use and do not "end".

In studies that focus on short-term impacts, such as maternal exposure and infant mortality (e.g. (Bharadwaj et al., 2020; Von Der Goltz et al., 2020; Brainerd and Menon, 2014)) , treatment is often binary, comparing periods before and after an intervention. In contrast, my study deals with prolonged exposure throughout childhood. For example, I cannot observe a birth cohort exposed only in early childhood but not in later years. Instead, I compare cohorts with added exposure early in life, conditional on exposure later in childhood. To illustrate this, suppose an individual's health can be modeled as a function of exposure to Green Revolution technologies during two time periods: early childhood (period 1) and later life (period 2). My analysis compares cohorts born just before and after the Green Revolution in areas with higher potential productivity gains, relative to those in areas with lower gains. The treatment group, born after the Green Revolution, experiences full exposure in both periods, while the comparison group, born before, has no exposure in early childhood but the same exposure later. This comparison help me to isolate the impact of early-life exposure.

I also employ an event-study model to estimate the time-varying effects of potential productivity gains, controlling for birth year, district, along with district controls. It also helps validate the identification strategy by allowing me to estimate differential health trends before widespread HYV adoption. I group birth cohorts into three-year intervals and track the evolution of differences across districts, using those born between 1963 and 1965 as the reference group. I define six pre-1966 cohorts (1945-1947, 1948-1950, 1951-1953, 1954-1956, 1957-1959, and 1960-1962) and six post-1966 cohorts (1966-1968, 1969-1971, 1972-1974, 1975-1977, 1978-1980, 1981-1983) for the analysis. I estimate the following equation:

$$Y_{i,d,t} = \sum_{n=1}^{6} \theta_l^{pre} \left(\text{ProdGain\_wr}_d \times \gamma_n\right) + \sum_{n=8}^{13} \theta_l^{post} \left(\text{ProdGain\_wr}_d \times \gamma_n\right) + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{i,d,t} \quad (4)$$

where γ_n represents the birth cohort dummies, θ_l^{pre} and θ_l^{post} are the coefficients of interest for the pre- and post-1966 cohorts, respectively. Estimates of θ_l^{post} capture the differential health outcomes for individuals born in districts with higher potential productivity gains post-1966 and higher HYV adoption, relative to those born in districts with lower gains. θ_l^{pre} close to zero would support the validity of my identification strategy.

[18]Fertilizer exposure is an endogenous control, removing and keeping this control doesn't change the estimates. I use it in my preferend specification to rule out the fertilizer channel.

5. Results

5.1 Adoption of high-yielding varieties of wheat and rice

I begin by documenting the relationship between potential productivity gains and the adoption of HYV wheat and rice. I estimate equation 1 for the share of area planted using high yielding varieties of wheat and rice in total cultivated area and the results are shown in the Table 2. The first column includes exclusively the potential productivity gains and the fixed effects on the right hand side and suggests a strong relationship between HYV adoption of wheat and rice and potential productivity gains. The second column introduces a comprehensive set of controls, including annual mean precipitation, temperature, and various baseline district characteristics such as population density, agricultural wages, road density, literacy rates, the share of irrigated land, soil pH, and the area share of wheat and rice, as well as their respective yields, all interacted with year fixed effects. These controls help account for differential trends influenced by the districts' initial geographical and socio-economic contexts. Importantly, despite the inclusion of these controls—aimed at capturing the effects of initial conditions on trends in HYV adoption—the core relationship remains robust in both magnitude and statistical significance. A one standard deviation increase in potential productivity gains (1.26 tonnes per hectare) in wheat and rice leads to 5 percentage points increase in share of HYV adoption of wheat and rice.

Although high-yielding varieties (HYVs) were not introduced in India until 1966, I estimate equation 2to explore the relationship between potential productivity gains and the share of HYV adoption for wheat and rice in the periods following 1965. Figure 6 illustrates the trend in HYV adoption in total cultivated area over time. Before 1966, the area planted with HYVs was zero across all districts, indicating no differential trends prior to the Green Revolution. I conduct a similar regression from 1957 to 2007 to analyze the relationship between potential productivity gains and the share of area under wheat and rice. Since direct data on HYV adoption before 1966 is unavailable, this regression serves as a proxy for pre-existing trends. Appendix Figures A.8 and A.9 show no significant pre-trends.

It's important to note that potential productivity gains are based on theoretical models of potential yield, calculated using climatic characteristics. As a result, these values are unlikely to be influenced by endogenous factors or observed production patterns. Furthermore, I present evidence suggesting that the relationship between potential productivity gains and the share of HYV adoption is not affected by district-level variations in initial characteristics.

5.2 Effect on crop diversity

After establishing that potential productivity gains strongly predict HYV adoption, I examine their relationship with crop diversity. Table 3 estimates the equation 1, analyzing the effect of potential productivity gains on crop diversity, measured by the shannon diversity index. Column (1) shows a strong negative relationship between crop diversity and potential productivity gains, with only fixed effects included. In Column (2), I add controls for initial geographical and socio-economic characteristics, and the negative relationship remains strong in both magnitude and statistical significance. Assuming an equal distribution of crops, a mean Shannon diversity index (DI) of 1.5 equates to 4.5 crops. A one standard deviation increase in potential productivity gains (1.26 tonnes per hectare) reduces crop diversity from 4.5 to 3.8 crops. Additionally, a simpler analysis using the number of crops as the dependent variable (Appendix Table A.1) shows that full potential productivity gains (8 tonnes per hectare) would reduce crop diversity from 4.3 to 2 crops. [19]

To further validate the empirical strategy, I estimate the flexible specification in equation 2. This approach enables me to examine whether districts with higher potential productivity gains showed different trends in crop diversity before the introduction of HYVs. The absence of such pre-existing trends supports the key assumption that, without the Green Revolution, districts with varying levels of exposure to productivity gains would have followed similar crop diversity trajectories. If the adoption of Green Revolution technologies impacted district outcomes, we would expect districts with higher productivity gains in wheat and rice to diverge from others starting in 1966.

In Figure 7, the estimated coefficients remain near zero and statistically insignificant before the introduction of HYVs, indicated by the period prior to the vertical line. This suggests that potential productivity gains from the shift to Green Revolution technologies were not linked to any pre-existing trends in crop diversity. Districts more suited for HYV adoption followed similar crop diversity trajectories as those less suited before the Green Revolution. However, after the release of HYVs, crop diversity declines significantly, with the effect intensifying over time.

Drivers of Declining Crop Diversity: Which Crops Are Losing Ground?

Building on the analysis of the overall decline in crop diversity, I now examine which specific crops experienced a reduction in cultivated area. Different crops are grown in distinct seasons, and potential productivity gains from adopting HYV wheat and rice may drive crop substitution. For example, in the Rabi (winter) season, wheat, barley, and chickpea are cultivated. As productivity gains from wheat increase, farmers might shift land from barley and chickpea to wheat. Similarly, in the Kharif (monsoon) season, crops like rice, maize, pearl millet, and sorghum are grown. Higher potential gains from rice could lead to more land allocated for rice at the expense of other Kharif crops. To analyze this, I estimate a similar equation to 1, using the area under specific consumption crops as the dependent variable. [20] This analysis will highlight the shifts in crop cultivation, revealing which crops were most impacted by the likely adoption of high-yielding wheat and rice varieties. Figure 8 shows the effect on area under different consumption crops.

The results indicate that as potential productivity gains increase, the area dedicated to wheat and rice expands, while the area for barley, pearl millet, chickpea, minor pulses, and groundnut decreases.

[19] If all crops are equally distributed on the area cropped, the crop diversity formula turns into ln(n). At the mean crop diversity of 1.5 in the sample, the corresponding n value is 4.8. A 1 s.d. increase in potential productivity gains leads to a decline in crop diversity value by ≈ 0.12 ((1.3)*(0.09)). At the mean crop diversity, this implies a reduction from 1.5 to 1.38. The corresponding n here is 3.8

[20] Since the focus of this paper is on the health outcomes, I show the results for consumption crops and exclude cash crops from the figure. I analyze the area under following crops: Barley, finger millet, maize, sorghum, pearl millet, chickpea, pigeonpea, minorpulses, potatoes, onion, groundnut, soybean, wheat and rice.

Declining Crop Diversity and Shifts in Production

After establishing that the area under certain crops has declined while wheat and rice have expanded, I now turn to examining the overall production of these crops. Figure 9 indicates a statistically significant decline in the production (measured in tonnes) of pearl millet, chickpea, minor pulses, pigeonpea, and groundnut. Barley and finger millet production has decreased, though these reductions are statistically insignificant. Maize and sorghum production has slightly increased. This decline in the production of various crops may limit the availability of diverse food options, potentially impacting dietary variety and nutritional access.

Despite the decline in production of certain consumption crops, imports may have been sufficient to sustain overall availability. Although district-level data on imports and exports is unavailable, ICRISAT provides national-level data on per capita availability (kg/year), which is defined as production plus net imports per capita for the period from 1951 to 2006. This data is divided into four main categories: wheat, rice, coarse cereals (including millets, maize, and sorghum), and lentils. I plot the trends in per capita availability (kg/year) for these food groups to examine how changes in production and imports have impacted overall availability. Appendix Figure A.10 illustrates that, while per capita availability of wheat and rice has increased, availability has decreased for lentils and coarse cereals. This trend further supports the argument that the availability of diverse food options is becoming limited.

Availability of Nutrients

Lentils, barley, and pearl millet provide unique nutritional benefits compared to wheat and rice, particularly in terms of protein content and essential micronutrients. To assess the impact of these production changes on caloric and nutritional availability, I run equation 1 using the caloric and nutrient equivalents of the sum of these consumption crops as the dependent variables. Table 4 presents the result from the estimation. The results show that exposure to higher potential productivity gains increased calorie production by 20% and carbohydrate supply per calorie by 0.6%. However, protein supply per calorie declined by 3%. Additionally, iron decreased by 2%, folate by 9%, and zinc by 2%.[21]

I estimate the coefficients from the flexible specification in equation 2 for each outcome variable related to calories and nutrients. Figures 10 -16 show the time-varying effects of potential productivity gains on calorie and nutrient availability per calorie. I find three key results: First, trends in all outcomes between the treatment and control groups were nearly identical before the Green Revolution, reinforcing the model's identifying assumption that, without the Green Revolution, caloric and nutrient outcomes would have followed similar trajectories. Second, following the Green Revolution, there is a mean increase in total calories and carbohydrates per calorie produced. Third, there is a mean decrease in protein, zinc, iron, and folate per calorie produced.

[21] When considering consumption, what matters is the nutrient intake received per calorie available, rather than total nutrient production.

5.3 Effect on Health Outcomes

After presenting the results on nutrient availability, I assess the impact of these potential changes on health outcomes, guided by the early origins of disease hypothesis. I first provide evidence on the effects on height, metabolic syndrome, cognition, and motor skills, followed by an analysis of placebo health outcomes.

Adult Height

Height provides a summary measure of the stock of nutritional investments made during an individual's early years of life and is associated with increased living standards, increased life expectancy, and decreased mortality.

Table 6 estimates equation (3) to analyze the relationship between potential productivity gains and height measured in cms. The first column includes individual controls, district and year of birth fixed effects, and the second column also includes district controls for precipitation, temperature, and fertilizer exposure at the year of birth. A one standard deviation increase in potential productivity gains (2.14 tonnes per hectares) leads to a 0.4 cm decline in height. Cohorts born in districts with the highest productivity gains (7 tonnes per hectare) after the Green Revolution experience a 1.2 cm reduction in height. The negative effect on height is particularly revealing, as it suggests that while wheat and rice may have provided sufficient calories, there was likely a shift away from protein- and micronutrient-rich foods toward a diet more reliant on wheat and rice, which are predominantly carbohydrate-rich. Empirical evidence demonstrates that malnutrition, particularly deficiencies in essential nutrients, can adversely affect fetal growth and development. Despite potential improvements in calorie intake, the adverse effects of nutritional deficiencies appear to have outweighed these gains, ultimately leading to a negative effect on height.

These estimates align with findings from the literature on early-life nutritional and income shocks on height. For example, Banerjee et al. (2010) report that individuals born in regions affected by the phylloxera crisis in French vineyards were 0.18 cm shorter. Similarly, Maccini and Yang (2009) find that women born in years of higher-than-normal rainfall were 0.57 cm taller. Additionally, Nunn and Qian (2011) show that the introduction of potatoes increased adult height by 1.78 cm in fully suitable towns, which is comparable to the 1.2 cm decline found in my results.

In India, average height has increased only modestly over the past century—women's height rose by 5 cm, from 147 cm to 152 cm, while men's height grew by just 3 cm, from 161 cm to 164 cm. Despite India outperforming many African countries in key development indicators, height disparities between the regions remain significant. Jayachandran and Pande (2017) highlight the role of gender-based birth-order differences and son-preferences in explaining these height gaps, particularly in India. My findings offer further evidence of persistent nutritional inadequacies that may contribute to these ongoing height disparities, pointing to another factor behind lower average Indian heights.

Table A.2 shows the result for the effect of potential productivity gains on adult stunting-an indicator variable defined as having a height lower than 2 standard deviations below the gender-specific average based on the Indian DHS 2004-05 data. While the estimates are positive, the effect is statistically insignificant.

Metabolic Syndrome

Next, I examine the effect of potential productivity gains on metabolic syndrome index (MSI). The MSI is calculated as the equal-weighted average of the z-scores for seven dichotomous variables: BMI-based obesity, obesity based on waist-hip circumference ratio, diabetes, hypertension, chronic heart conditions, and high cholesterol.

Table 7 the results of my analysis on how potential productivity gains affect the MSI and its components. It includes district controls for precipitation, temperature, and fertilizer exposure at the year of birth along with district of birth and year of birth fixed effects.[22] I find that potential productivity gains significantly impact the MSI, with a coefficient of 0.012, which is statistically significant at the 5% level. This coefficient suggests that a one standard deviation increase in potential productivity gains results in a 0.026 standard deviation increase in the MSI. I observe positive coefficients for all components of the MSI except chronic heart conditions. However, only the coefficients for hypertension and diabetes are statistically significant. Specifically, a one standard deviation increase in potential productivity gains is associated with a 3.7 percentage point increase in hypertension and a 1.5 percentage point increase in diabetes. My estimates align with Sekhri and Shastry (2024), who identified a 4 percentage point increase in diabetes prevalence among men born in groundwater-rich districts following the Green Revolution. In my analysis, males born post-1966 in districts with the highest potential productivity gains exhibit a 4.9 percentage point increase in diabetes prevalence.

Cognition and Motor Skills

Given that nutrient deficiencies can affect cognitive development and motor skills, I also examine the effects of potential productivity gains on cognitive imbalance and motor function deficit using the LASI data. Column 1 of Table 8 shows the effect on cognitive imbalance index (CII). The CII is calculated as the equal-weighted average of the z-scores for three dichotomous variables: neurological disorder, cognitive score(<15) and, cognitive score(<19). Although the effect is positive, it is statistically insignificant. Column 2 shows the effect on neurological disorder, which is positive but also statistically insignificant.

Column 1 of Table 9 shows the effect on motor deficit index (MDI). The MDI is calculated as the equal-weighted average of the z-scores for two dichotomous variables: grip strength deficit and balance deficit. The effect on overall deficit is positive, but statistically insignificant. Column 2 shows the effect on grip strength deficit, which is positive and statistically significant at 10%. Overall, the results suggest that potential productivity gains have a limited effect on cognitive imbalance and motor function deficit.

[22]The results after removing the fertilizer exposure at birth are essentially identical. I include it in my preferred specification to rule out the fertilizer channel.

Placebo Health Outcomes

To validate the robustness of my findings, I analyze health outcomes unrelated to early childhood exposure as a placebo check. I evaluate the impact of potential productivity gains on the likelihood of experiencing physical injuries or disaster-related health risks. The results presented in Table A.23 indicate that there is no significant effect of potential productivity gains on these health risks.

Event Study Analysis

The results from the estimating equations thus far measure exposure to potential productivity gains based on whether individuals were born in years post-1965, when the effects from HYV wheat and rice adoption would be realized in the district of birth. While these regressions control for fixed differences across districts and years, interpreting these estimates as the effect of the Green Revolution requires assuming parallel trends between districts with different levels of potential productivity gains. To address that, I estimate equation (4) for the health outcomes to examine the time-varying effects of potential productivity gains and check for the presence of pre-trends.

Appendix Figure A.13 show the event-study estimates for the effect on height. There are two key findings. First, the pre-Green Revolution trends for treatment and control cohorts are nearly identical, reinforcing the identifying assumption—that in the absence of the Green Revolution, outcomes between the two groups would have evolved similarly. Second, following the Green Revolution, we observe a decline in height. The transitional dynamics suggest that exposure to potential productivity gains from the Green Revolution between conception and age 1 leads to larger reductions in height compared to exposure after age 1. In contrast, no negative effects are found for cohorts born before 1966, indicating minimal impact on height from exposure beginning after age 1.

Appendix Figures A.15 and A.16 show the event-study estimates for the effect on diabetes and hypertension. For diabetes, the trends between treatment and control cohorts prior to the Green Revolution are nearly identical. However, after 1966, there is a notable increase in diabetes incidence, suggesting that exposure to potential productivity gains from the Green Revolution between conception and age 1 leads to a higher risk of diabetes compared to exposure after age 1. Specifically, I observe a slight increase in diabetes among cohorts born between 1966-1968, no effect for those born between 1969-1970, and a consistent rise in incidence estimates for cohorts born after 1970.

For hypertension, I observe some significant differences among cohorts born prior to the Green Revolution, with nearly all coefficients—especially the significant ones—showing negative values. This indicates that younger individuals born in districts with higher potential productivity gains are less likely to be diagnosed with hypertension. In fact, the differential pre-trends seem to move in the opposite direction. cohorts born after the Green Revolution show a notable secular increase in hypertension incidence estimates.

Appendix Figure A.18 show the event-study estimates for the effect on neurological issue. The pre-Green Revolution trends for treatment and control cohorts are nearly identical, supporting the assumption that, in the absence of the Green Revolution, outcomes would have evolved similarly. I find no increase in neurological issues for cohorts born between 1966 and 1971; however, there is a rise in incidence for those born after 1971. This suggests that exposure to potential productivity gains from the Green Revolution between conception and age 1 is linked to a higher incidence of neurological issues, particularly for cohorts born after 1970.

5.4 Identification Threats

Trends in Processed Food Consumption, Lifestyle, and Health Care Availability

A potential threat to my identification strategy arises if recent trends in dietary habits, such as increased consumption of processed foods, and lifestyle changes—characterized by more sedentary jobs and reduced physical activity—are correlated with potential productivity gains from wheat and rice following the Green Revolution. Additionally, if differential access to health care aligns with districts experiencing higher productivity gains, these factors could confound the estimated effects.

To mitigate these potential confounding factors, I control for several baseline characteristics that may influence both dietary and health trends. Specifically, I include the share of the urban population, the share of the literate population, the proportion of employment in the service sector, and access to public health care at baseline, each interacted with a linear cohort. These controls account for evolving socio-economic and lifestyle factors that may be correlated with both the relative gains in potential productivity and the observed health outcomes, thereby ensuring that the estimated effects of HYV adoption are not driven by these broader trends.

Appendix Tables A.28- A.31 present the results of the effects of potential productivity gains on height, the metabolic syndrome index, cognitive imbalance index, and motor deficit index, while controlling for trends in urban population share, literacy rates, and employment in the service sector. The effect on height remains stable and statistically significant at the 10% level. Estimates for the metabolic syndrome index are positive but not statistically significant. Among its components, the estimate for hypertension is both positive and significant at the 5% level. Additionally, the estimates for the cognitive imbalance index and motor deficit index are positive but statistically insignificant.

Appendix Tables A.32- A.35 present the results of the effects of potential productivity gains on height, metabolic syndrome index, cognitive imbalance index, and motor deficit index, while controlling for trends in the share of health care centers. Due to the availability of baseline data on the share of health care centers for only 140 districts, the number of observations decreases. Nevertheless, the results remain consistent with previous findings. The effect on height is negative and statistically significant at the 1% level. Additionally, the estimates for hypertension are positive and significant at the 5% level. I also observe a statistically significant positive effect on the likelihood of receiving a lower score on the cognitive evaluation. For motor deficit, the effect is positive and statistically significant at the 5% level, primarily driven by deficits in grip strength.

Migration Patterns

Being born in a district that experienced significant productivity gains due to the Green Revolution may lead to differing migration patterns across regions. My results may be biased if the Green Revolution influences the likelihood that an individual migrates out of the sample districts.

Spillovers

Another concern in the estimation of the effects of Green Revolution on health outcomes is the potential for spillovers across districts, which could violate the Stable Unit Treatment Value Assumption (SUTVA). In this context, SUTVA would be violated if changes in agricultural production or nutritional availability in one district influence outcomes in other districts. For instance, increased adoption of high-yielding variety (HYV) crops in one district may lead to changes in food availability and prices in neighboring districts through market integration. This could result in changes in health outcomes in those areas, even if the neighboring districts did not adopt HYV crops to the same extent. Nutritional spillovers may also occur when surplus production from HYV adoption in one district benefits neighboring districts by improving local food availability. If it results in dietary diversification in neighboring control districts and potentially improves health outcomes, it could introduce an upward bias in the estimates. I address this concern in three ways.

First, as noted earlier, market integration in India during the 1960s was poor. Kapur and Chatterjee (2016) provides evidence of spatial price dispersion for agricultural commodities between 2005 and 2014, long after the Green Revolution and subsequent economic liberalization in 1990s. Using high-frequency price data of various food crops they show that price variation among agricultural markets, or mandis, has remained high across different crops over the past decade. Furthermore, they provide evidence of high within-state variation underscoring the limited market integration. This suggests that the potential for spillovers across districts between 1945-1985 due to changes in agricultural production or nutritional availability is likely to be minimal.

Nonetheless, I add road length at the baseline as a proxy for trade and market integration in a district and interact it with linear cohort as a control to account for potential trade from other districts. The results remain consistent even after adding this control. However, If neighboring treatment districts have enhanced road infrastructure, they may affect trade and outcomes in the control district, which would be overlooked if we only consider the district's own road length. To address this, I will include the average road length of neighboring districts as a control variable. Furthermore, I will incorporate the baseline share of individuals employed in the trade and commerce sector, interacted with a linear cohort, as a proxy for trade and market integration to account for potential influences from trade in surrounding districts.

Envisioning further threats to the identification strategy is challenging, as these would need to explain the differences in health outcomes between districts with varying potential productivity gains for those born just after 1966, while having no effect on individuals born before that time. Nonetheless, I perform a stringent analysis by including district-specific trends, which captures any time-varying factors that may not have been previously considered. Appendix Tables A.24- A.27 present the findings after controlling for these district trends. The negative effect on height remains consistent in magnitude but loses statistical significance following the inclusion of district trends. This change in significance likely reflects a reduction in statistical power due to these additional controls. However, the coefficient for the metabolic syndrome index changes sign after incorporating district trends, suggesting sensitivity to these trends. This sign reversal may indicate that district trends are capturing much of the variation in the independent variable. Results for cognitive imbalance and motor deficit remain positive but are statistically insignificant.

5.5 Treatment Effect Heterogeneity

Gender

First, I explore heterogeneity by gender by interacting the key treatment variable with indicator for if an individual is female. I explore treatment effect heterogeneity in a variety of ways. Table A.3 shows that while the negative relationship is statistically significant for both males and females, the estimates are higher for males. One potential explanation for the height differences between males and females lies in medical literature. Studies in both animals and humans indicate that male fetuses are more vulnerable to prenatal adversities due to their higher growth demands (Dearden et al., 2018; Alur, 2019). This vulnerability could explain the stronger effects of nutritional inadequacy on height reduction observed in males. Additionally, Table A.4 show that there is little to no treatment effect heterogeneity across gender for metabolic syndrome index. Appendix Table A.6 also shows stronger effect for males.

Family Background

Next, I examine the heterogeneity of effects based on the family background. Appendix Tables A.7-A.10 present results by interacting the key treatment variable with indicator for if an individual grew up in lower-income family during childhood. I find no evidence of treatment effect heterogeneity for height. In fact, the interaction coefficient is positive. However, for the metabolic syndrome index and motor deficit index, the effects are stronger and more pronounced for individuals from lower-income families. This indicates that individuals born after the Green Revolution in districts with higher potential productivity gains, and from lower-income families, are more likely to exhibit higher incidences of diabetes, hypertension, and motor deficits.

Religion

Next, I examine the heterogeneity of effects based on religion, as dietary practices differ between Hindus, who are more likely to follow entirely plant-based diets, than non-Hindus. Changes in nutritional availability from plant-based sources may therefore disproportionately impact Hindus. Appendix Tables A.11-A.14 present the results by interacting the key treatment variable with an indicator for if an individual belongs to Hindu religion. I find no evidence of significant treatment effect heterogeneity. While the interaction coefficients suggest a greater decline in height and a higher incidence of metabolic syndrome among Hindus, these results are not statistically significant.

6. Mechanisms

6.1 Production to Dietary Shifts

Due to the limited availability of individual-level dietary data from the 1960s, I am unable to directly trace how diets changed for pregnant women or infants during that time. However, I provide indirect evidence suggesting that these dietary shifts contributed to adverse health outcomes. First, using household consumption data from 1999-2000, I show a strong correlation between district-level crop production and consumption patterns. Second, I show that in households using ration cards to purchase wheat, rice, and millets, individuals born after the Green Revolution in districts with higher productivity gains consume more rice per capita. Additionally, hypertension and diabetes are more prevalent in households with higher cereal expenditures and less common in those with higher spending on animal-based foods. Finally, comparing men born before and after the Green Revolution in high potential productivity gains districts, I provide suggestive evidence that those born later tend to consume fewer micronutrients than recommended.

6.2 Alternative Mechanisms

Other in-utero exposure

Green Revolution might have influenced height and other health outcomes through higher pesticide exposure which is unrelated to nutrition. For instance, shifts towards HYV wheat and rice because of higher potential productivity gains can lead to increased exposure to chemical pesticides and fertilizers. Exposure to agrochemicals, such as pesticides and fertilizers, can have detrimental effects on health, particularly during critical developmental periods. Studies have shown that early-life exposure to these chemicals may impair growth, leading to reduced height. Agrochemical exposure has also been linked to an increased risk of metabolic disorders, such as diabetes and hypertension, by disrupting endocrine functions. Additionally, neurotoxic effects of certain pesticides can negatively affect cognitive development, resulting in long-term cognitive deficits (Eskenazi et al., 2004; Jaacks et al., 2024; Calzada et al., 2023). I present evidence suggesting that agrochemicals are unlikely to be the main drivers of these results in three key ways. First, my preferred models control for fertilizer exposure at the birth-year and birth-district levels, and the results remain statistically significant after accounting for this factor. Second, drawing on the approach from Brainerd and Menon (2014), I examine whether individuals born during the peak months of fertilizer and pesticide application for wheat and rice sowing exhibit different health outcomes, as they would have been exposed to higher levels of agrochemicals. The results, presented in A.15- A.18, show no evidence of treatment effect heterogeneity based on birth during the sowing months. Third, I test whether individuals born in rural areas, where agrochemical exposure is more common, experience worse health outcomes compared to those born in urban areas. However, one concern here is that dietary changes may also be pronounced in rural areas, which can make the result difficult to interpret. Nevertheless, I explore this possibility by interacting the key treatment variable with an indicator for rural birth. The results, presented in Appendix Tables A.36-A.39, show smaller negative effects on height for rural-born individuals. Additionally, there is little to no impact on the metabolic syndrome, cognitive imbalance, and motor deficit indices, with some indications of lower incidence for rural-born individuals. The results suggest that agrochemical exposure is unlikely to be the main factor behind the observed health outcomes. One explanation for the smaller effects in rural areas is that improvements in caloric sufficiency may partially offset declines in nutritional quality, especially if rural areas had lower baseline caloric intake compared to urban areas.

Adult Health Behavior

To further understand mechanisms, I also explored how the effect of the Green Revolution exposure on health outcomes change if I control for adult health behaviors such as smoking, alcohol consumption, and exercise.[23] The estimated effects of potential productivity gains on health outcomes as shown in Appendix Tables A.19-A.22 are little changed when these additional variables are included.

Infant Mortality and Non-Random Selection in Health Outcomes

Bharadwaj et al. (2020) research on the Green Revolution in India show has shown that regions with higher HYV adoption experienced reductions in infant mortality rates. Consequently, cohorts born before and after the Green Revolution may have differing health outcomes, not solely due to nutritional changes, but also because of selection effects: infants who survived due to reduced mortality may have different health endowments, potentially influencing average cohort health outcomes. To account for this selection bias, I estimates my main regressions on a sample of individuals who would have survived regardless of the Green Revolution's impact. I adjust the sample by trimming the number of "extra" individuals who survived due to HYV adoption. First, I calculate the expected relative change in infant mortality due to adoption of HYV in districtS with higher potential productivity gains using estimates from Bharadwaj et al. (2020). In this analysis, I categorize districts with high potential productivity gains as those exceeding the mean of 5.7 tonnes per hectare. As shown in Table 2, districts with higher potential productivity gains experience a 9 percentage point increase in HYV adoption. Bharadwaj et al. (2020) find that a 20 percentage point increase in the area allocated to high-yield varieties results in a 0.5 percentage point reduction in infant mortality risk. Based on these estimates, my analysis predicts a reduction of 0.225 percentage points in infant mortality. Consequently, I adjust the population of individuals born after 1966 in districts with high potential productivity gains by this percentage, specifically targeting individuals from low-income families who are shorter than the mean height for their gender in the sample or who exhibit incidence of metabolic syndrome, cognitive issues, or motor deficits. The results of a difference-in-differences analysis are presented in the Appendix Tables, where I randomly drop selected observations and include bootstrapped 95% confidence intervals. The estimates are stable and statistically significant, suggesting that the results are not driven by selection effects.

[23] It might not be particularly relevant for height since the height growth stop after the age of 18.

7. Alternative Specifications

The results I have presented are based on a difference-in-difference design that examines cross-sectional variation in potential productivity gains, interacted with an indicator variable for years post-1966. However, given the gradual adoption of HYV of wheat and rice, I can also utilize continuous variation in potential gains based on time-dependent changes in global HYV adoption.

As an alternative specification, I incorporate exogenous time variation from the adoption of HYV of wheat and rice in South Asian countries—namely, Pakistan, Bangladesh, and Nepal— which is independent of district-level decisions in India. By interacting the adoption rates of these crops in neighboring countries with their respective potential productivity gains, I generate a continuous measure of potential productivity gains. The following regressor is employed in the estimating equation:

$$\text{ProdGain\_wr}_{d,t} = (\Delta P_{w,d} \times \text{HYV\_AR}_t^w) + (\Delta P_{r,d} \times \text{HYV\_AR}_t^r)$$

where HYV_AR_t^w, HYV_AR_t^r is the share of HYV wheat and rice area, summed across Bangladesh, Nepal, and Pakistan, reflects in total cultivated area of these countries.

I estimate equation (3) using continuous variation in potential productivity gains. Essentially, I compare the health outcomes of individuals from the same district, who experience varying levels of potential productivity gains based on their birth year, while controlling for unobserved shocks to health outcomes that may also vary by birth year.

Appendix Tables A.40- A.43 present the results regarding the impact of the new exposure variable on height, metabolic syndrome index, cognitive imbalance index, and motor deficit index. The findings indicate consistent effects, with magnitudes slightly larger than those observed in previous analyses. Notably, the negative impact on height and the positive effect on the metabolic syndrome index are statistically significant at the 1% level.

Additionally, a significant positive association is found between higher potential productivity gains and cognitive imbalance, suggesting an increased likelihood of neurological disorders. Specifically, a one standard deviation increase in potential productivity gains (2.04 tonnes per hectare) is associated with a 1 percentage point rise in the likelihood of reporting neurological disorders. The point estimates for the motor deficit index are also positive and significant at the 1% level, indicating that a one standard deviation increase in potential productivity gains results in an increase in motor deficits by 0.08 standard deviations.

8. Conclusion

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Tables and Figures

Figures

Figure 1: Share of land under HYV wheat and rice in total land under wheat and rice

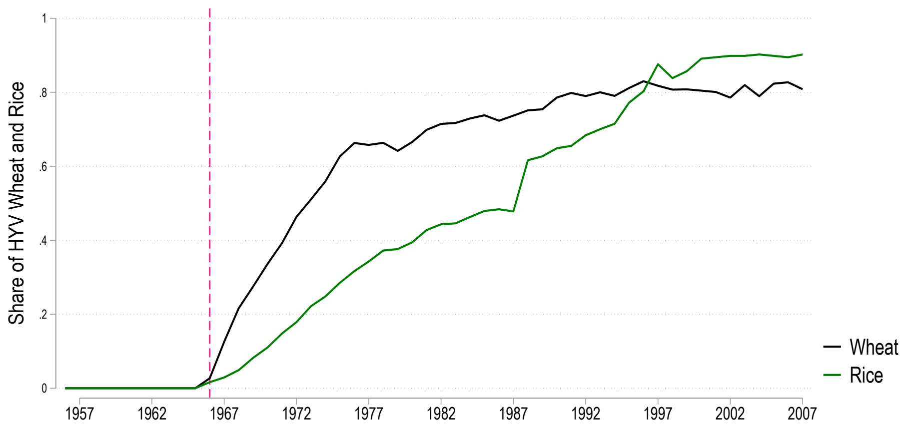
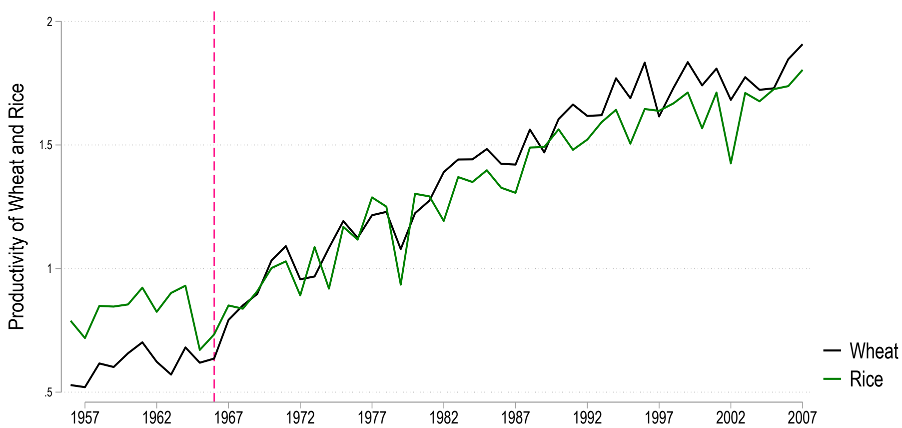
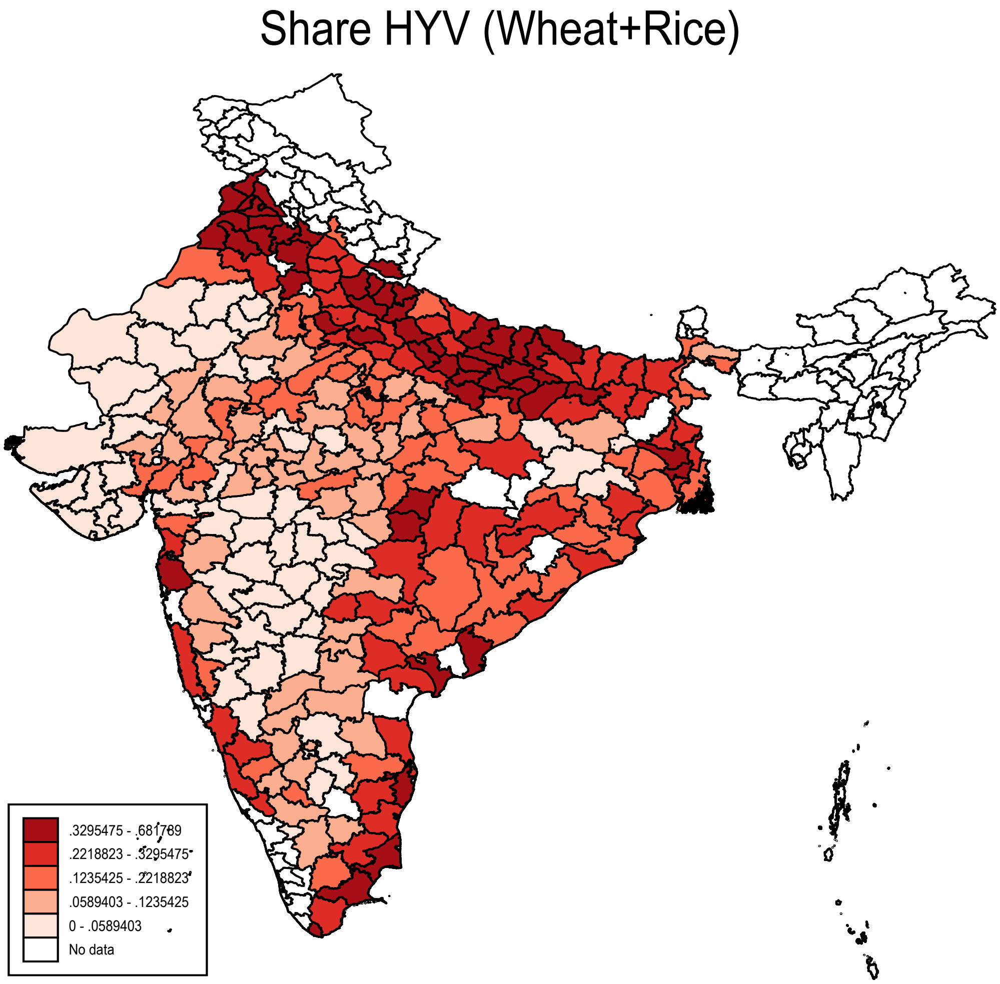


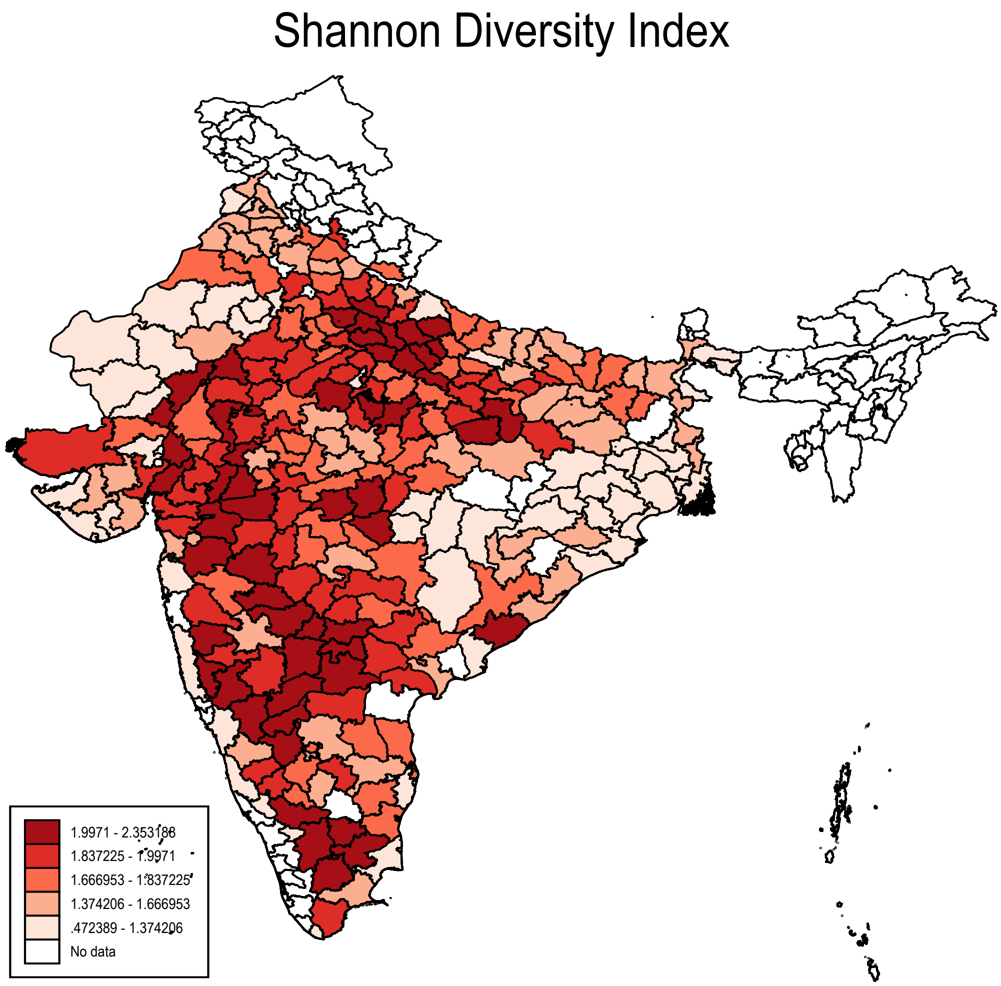
Figure 2: Productivity of wheat and rice (tonnes/hectares)





Source: Indian Agriculture and Climate Dataset

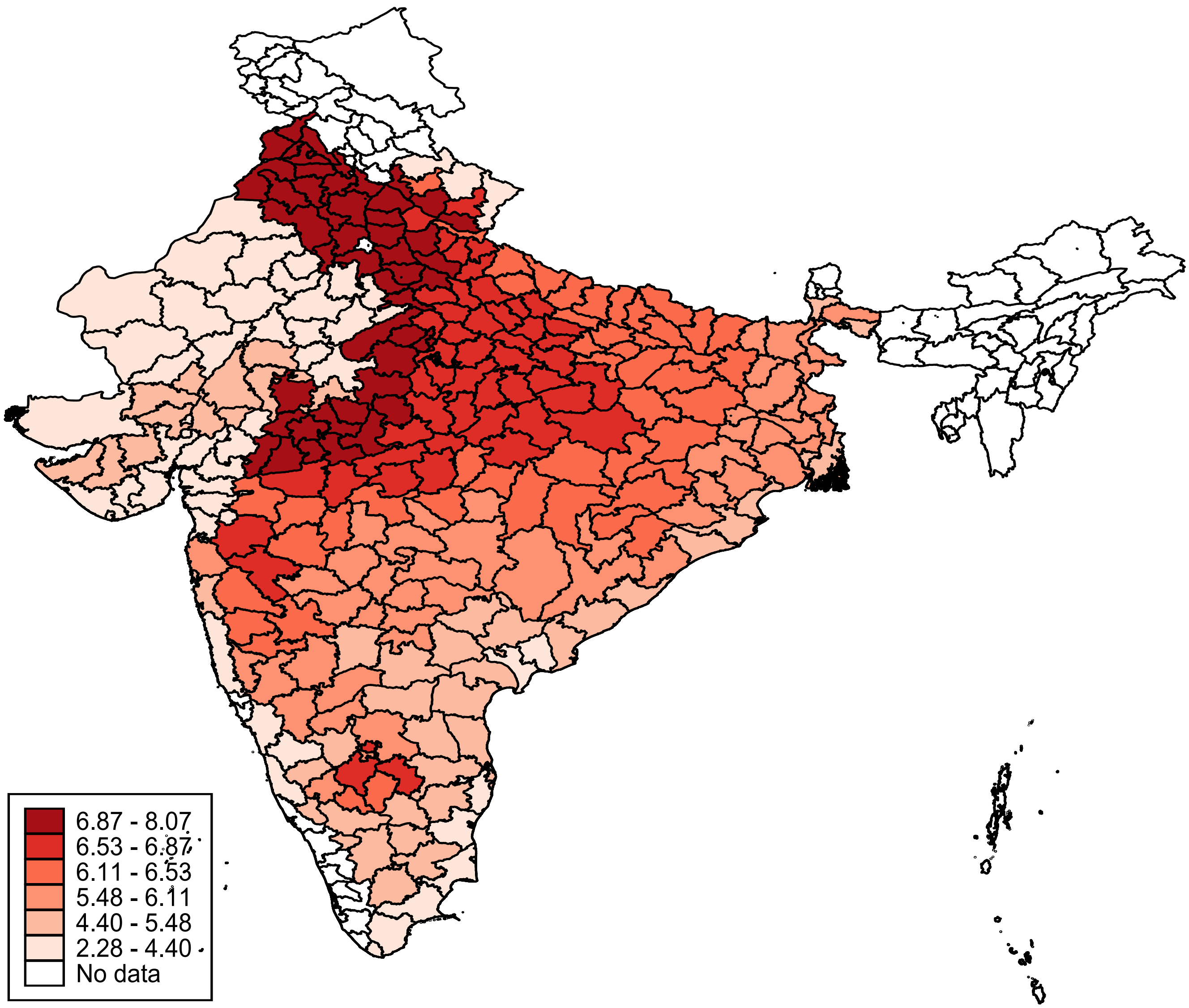
Figure 3: Average Share HYV adoption of wheat and rice in total cultivated area (1966-2007)



Source: Indian Agriculture and Climate Dataset

Figure 4: Average crop diversity measured between (1957-2007)

Figure 5: Geographic variation in potential productivity gains of wheat and rice



Notes: This map displays Indian districts in the IACD dataset (267 districts) shaded by potential productivity gains (000 kg/hc) calculated using FAO-GAEZ v4.0 dataset. Potential productivity gains are calculated as the average of gains for wheat and rice, measured by the difference between potential yields under low-input, rainfed conditions and high-input, irrigated conditions. Unshaded districts were not included in the IACD dataset. The lightest shade in north-western India reflects dryland rice measures in Rajasthan and Gujarat, as these states are predominantly arid or semi-arid. Wetland rice measures are used for the other regions.

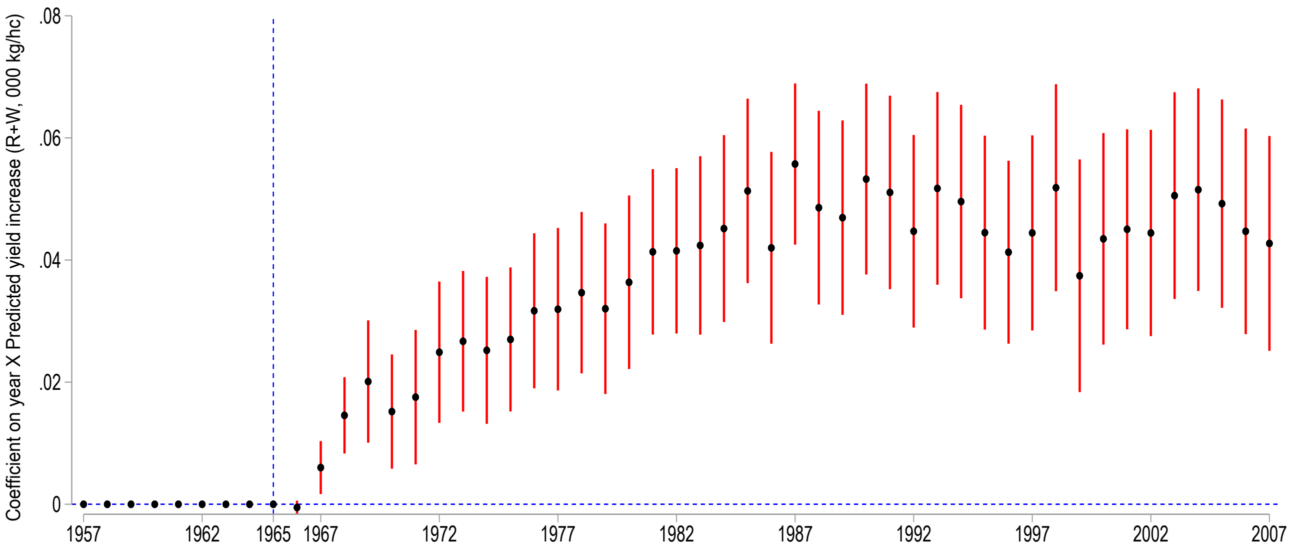
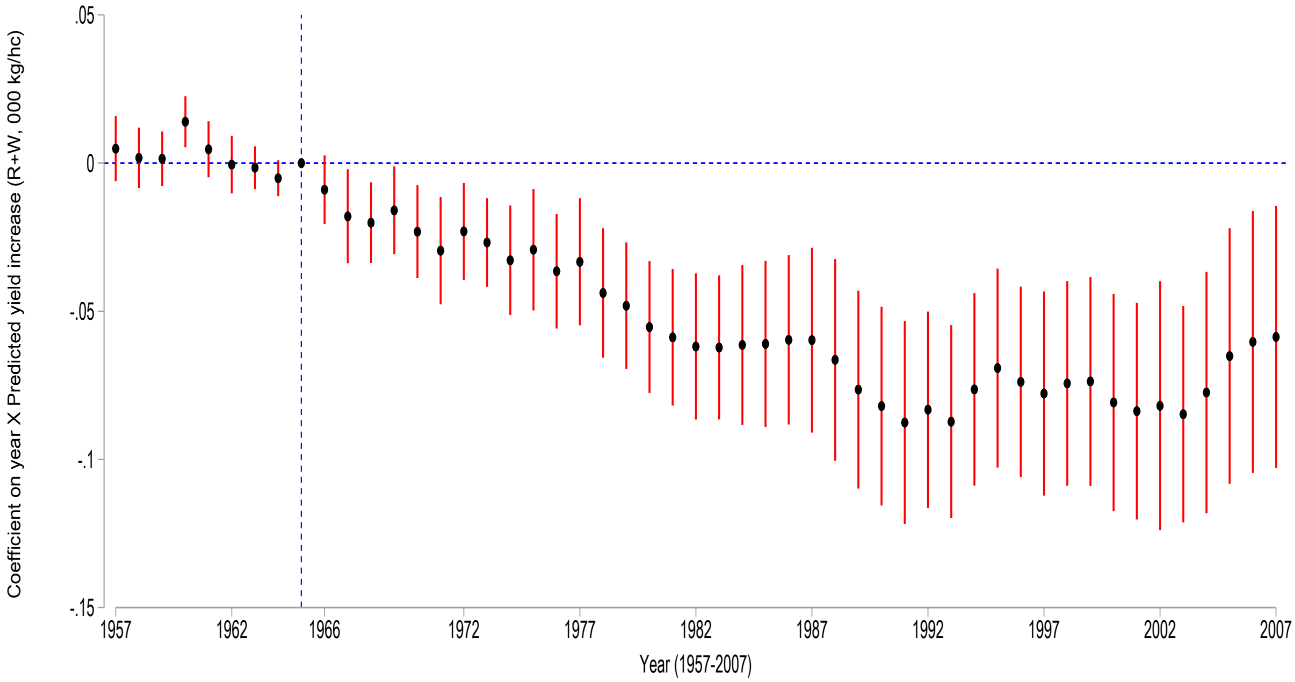


Figure 6: Event study estimates: Share of HYV adoption of wheat and rice in total cultivated area

Notes: This figure plots the coefficients from estimating equation 2 using share of area under HYV wheat and rice in total cultivated area as the dependant variable. The district level panel dataset from 1957-2007 has been used from IACD and ICRISAT. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 7: Event-study estimates for the effect on crop diversity



Notes: This figure plots the coefficients from estimating equation 2 using crop diversity as the dependant variable. The crop diversity is measured using shannon diveristy index=$\sum_{i=1}^{n} p_{i,d,t}\ ln(\frac{1}{p_{i,d,t}})$, where $p_{i,d,t}$ is the area planted under crop i in district d, year t. The data on share of area under each crop comes from district level panel dataset from IACD and ICRISAT. Total 21 crops (cash and consumption crops) are included in the measure accounting for 95% of production in India. The explanatory variable is potential productivity gains (000 kgs/hc) measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 8: Effect on area (in hectares) under different consumption crops

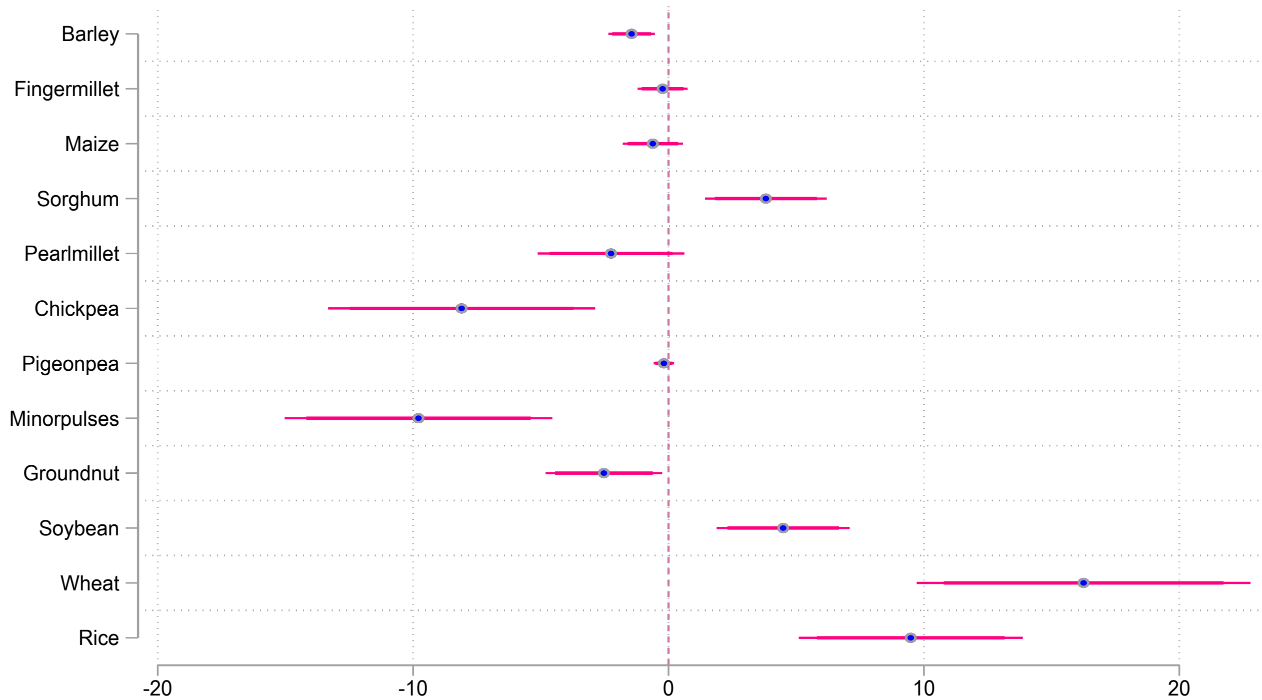


Figure 9: Effect on production (in tonnes) of consumption crops

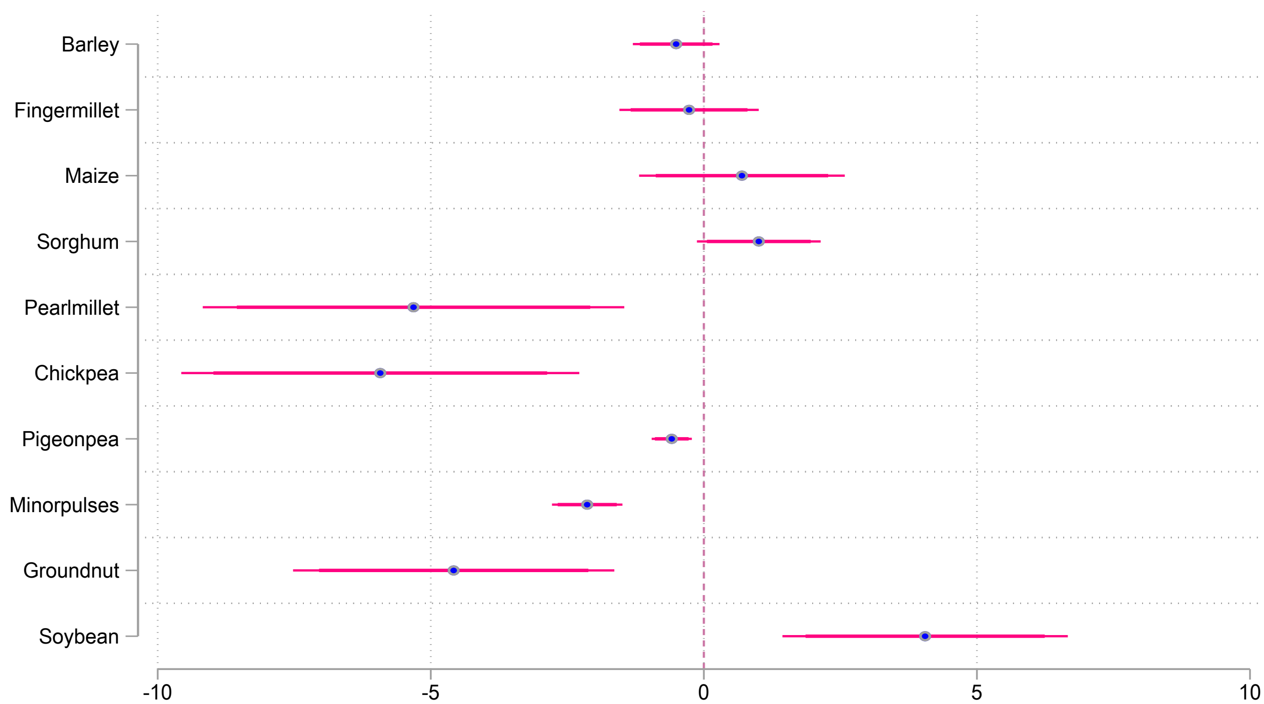
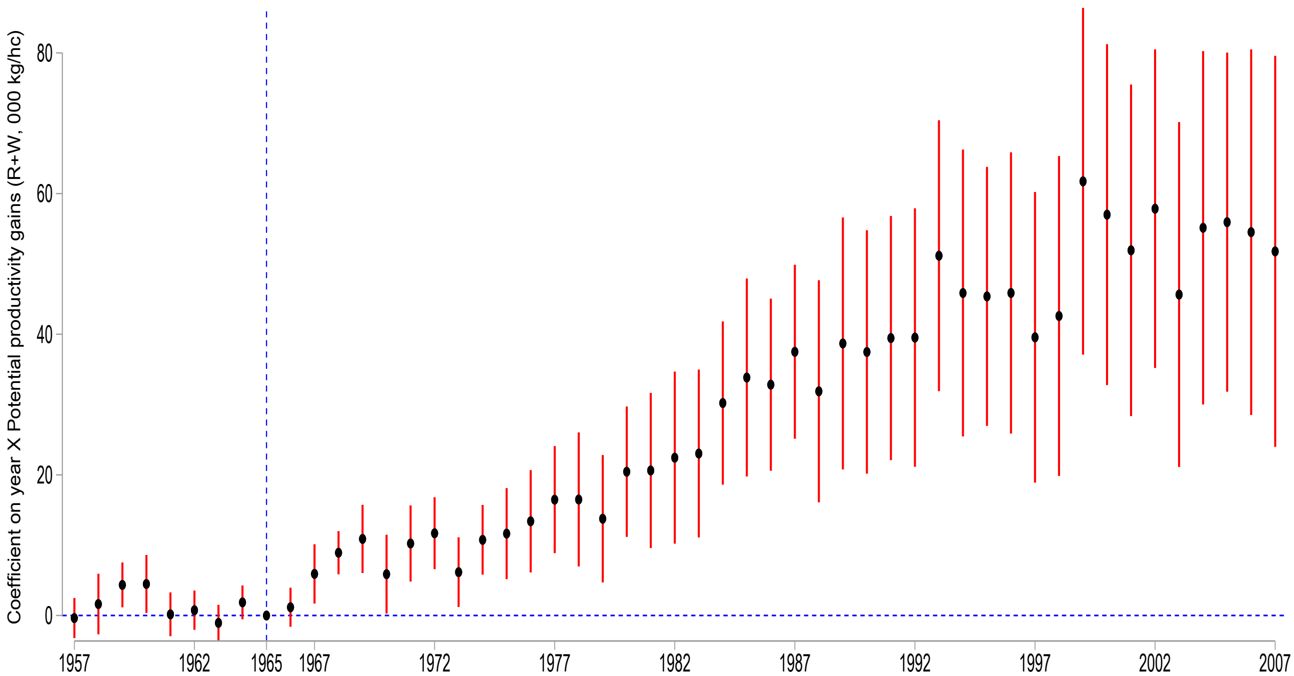
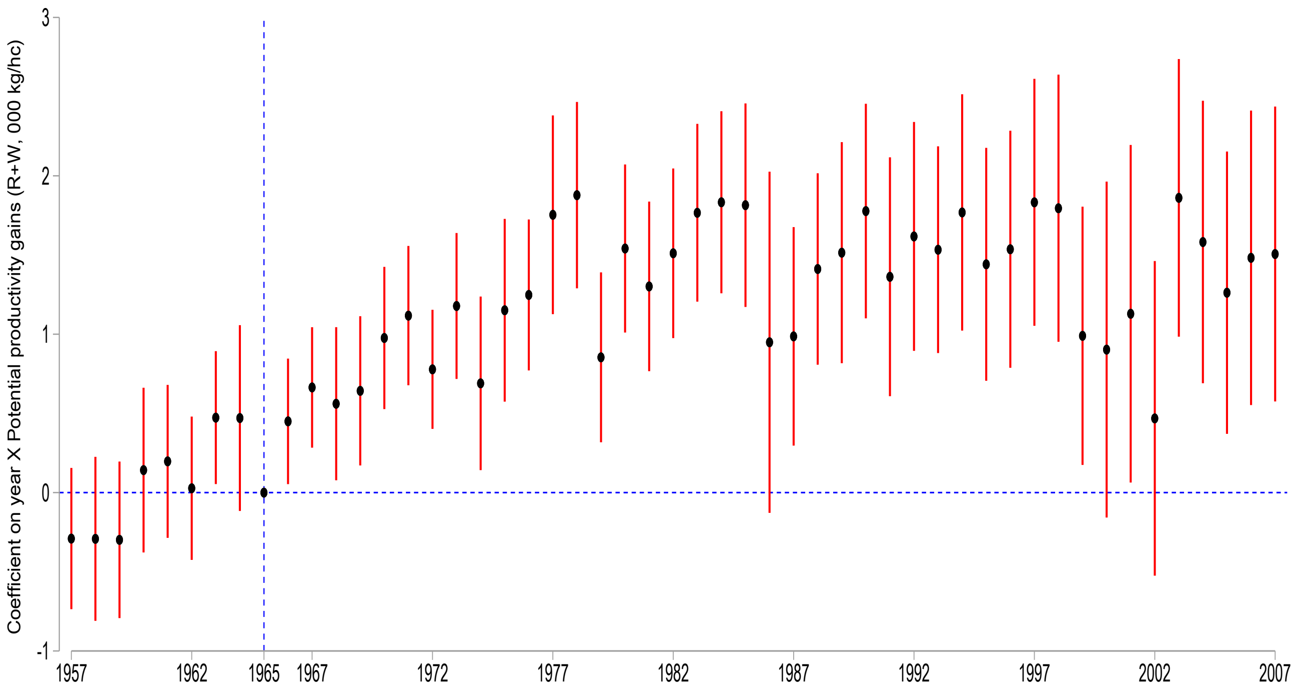


Figure 10: Event study estimates of total calorie production



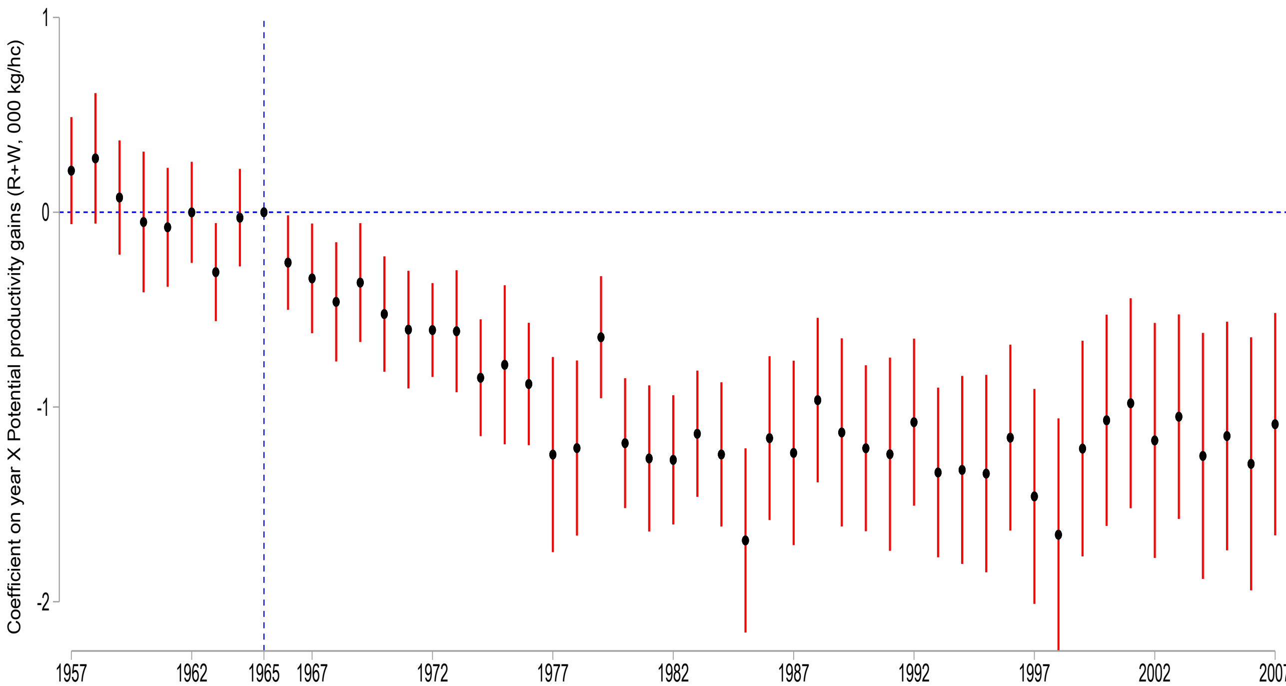
Notes: This figure plots the coefficients from estimating equation 2 using total calorie produced (000 kcal) as the dependant variable. The caloric calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 11: Event study estimates of carbohydrates per calorie produced



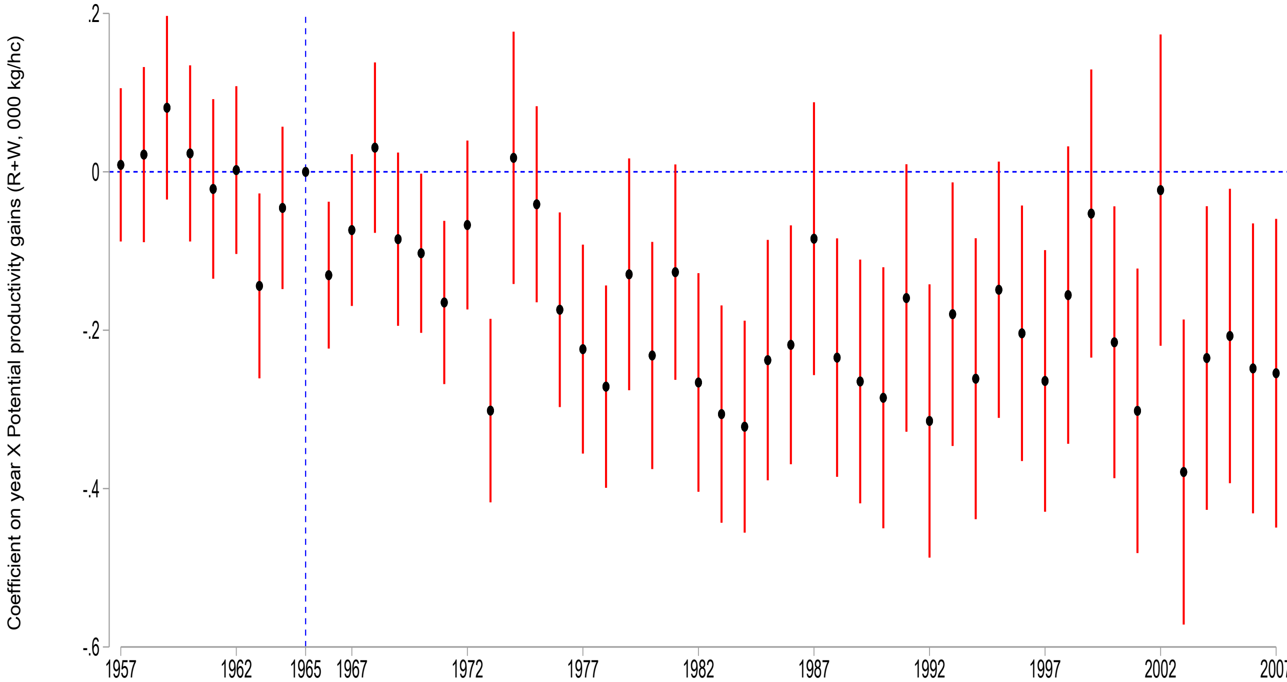
Notes: This figure plots the coefficients from estimating equation 2 using carbohydrate produced per calorie produced (g/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 12: Event study estimates of protein per calorie produced



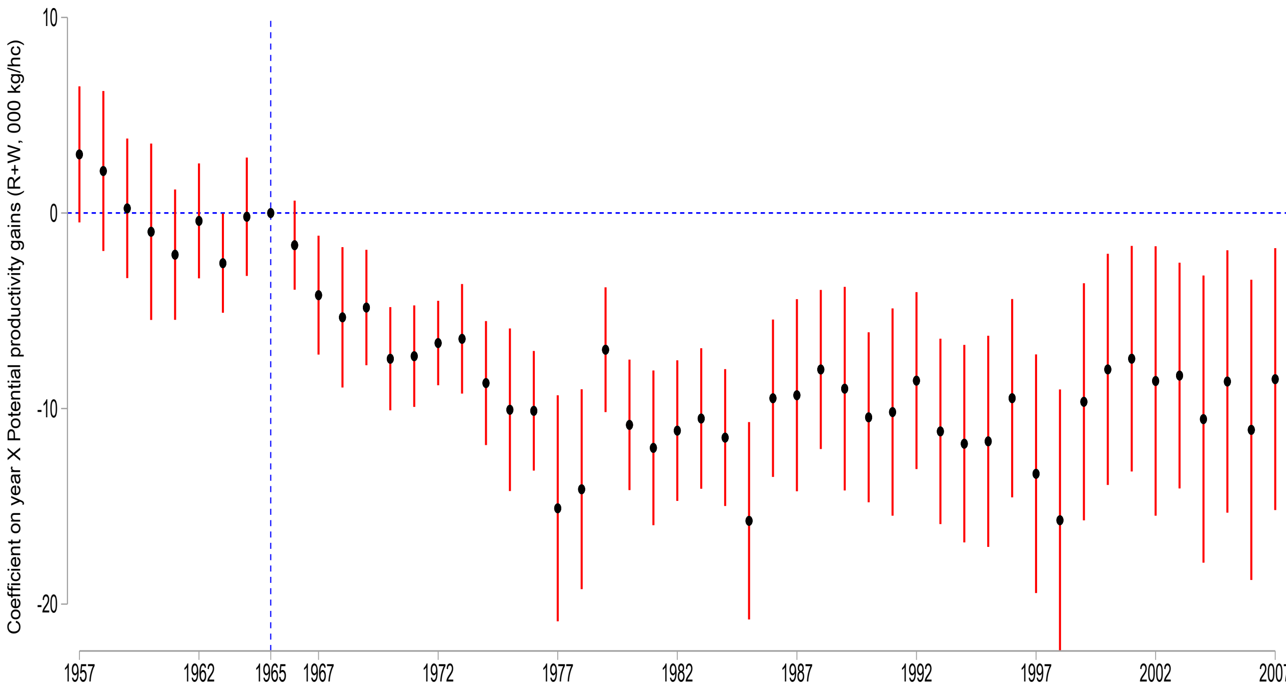
Notes: This figure plots the coefficients from estimating equation 2 using protein produced per calorie produced (g/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 13: Event study estimates of iron per calorie produced



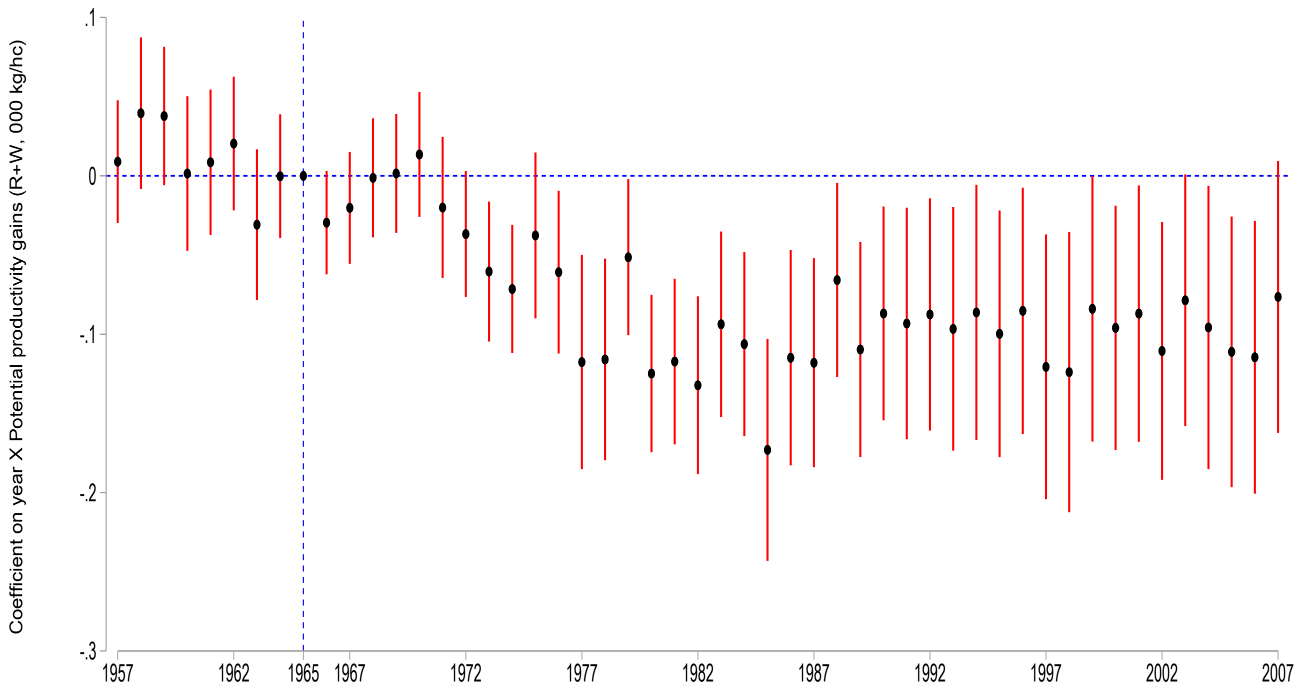
Notes: This figure plots the coefficients from estimating equation 2 using iron produced per calorie produced (mg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 14: Event study estimates of folate per calorie produced



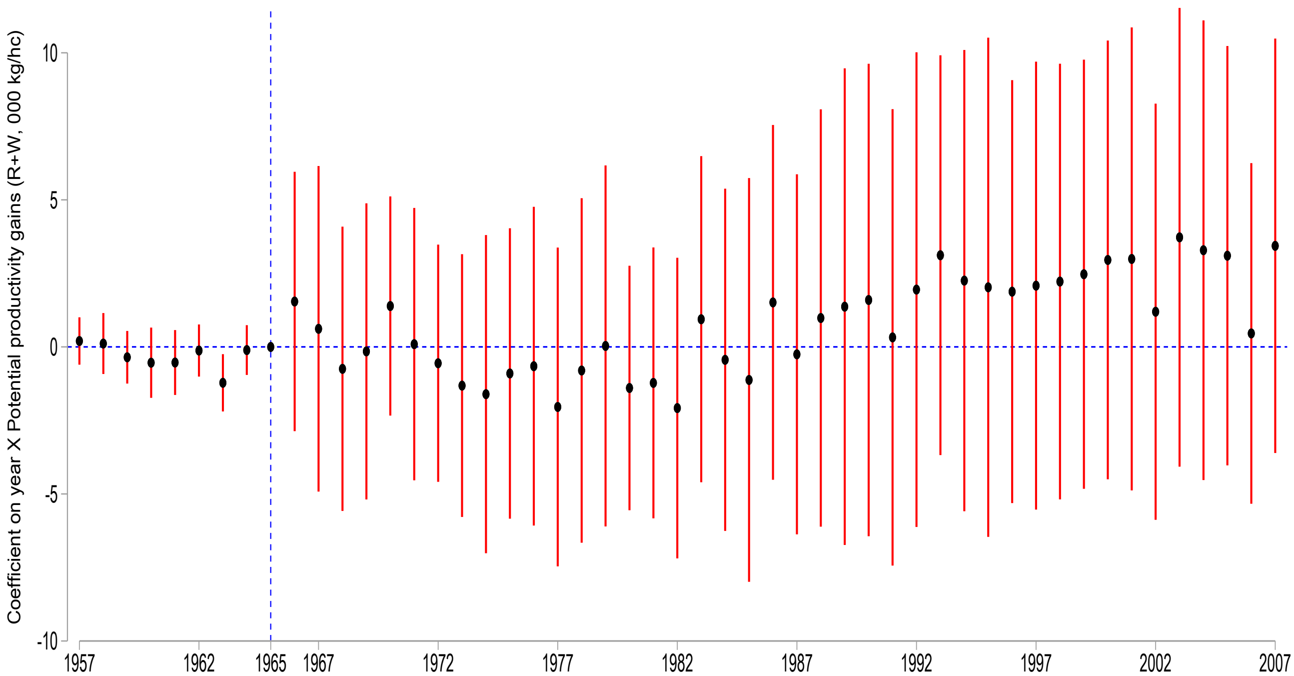
Notes: This figure plots the coefficients from estimating equation 2 using folate produced per calorie produced (μg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 15: Event study estimates of zinc per calorie produced



Notes: This figure plots the coefficients from estimating equation 2 using zinc produced per calorie produced (mg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 16: Event study estimates of calcium per calorie produced



Notes: This figure plots the coefficients from estimating equation 2 using calcium produced per calorie produced (mg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Tables

Table 1: Longetudinal Aging Survey of India: Summary Statistics

	N	Mean	s.d.
Age	41919	55.56	9.10
Born in rural area	41919	0.52	0.50
Female=1	41919	0.58	0.49
Hindu=1	41919	0.83	0.38
Lower caste=1	41919	0.29	0.45
High school educated	41919	0.68	0.47
Good family financial condition=1	41919	0.58	0.49
Migrated	41919	0.26	0.44
Migrated to another district	41919	0.13	0.34
Migrated to another state	41919	0.13	0.33
Height cms	38071	155.69	8.82
Height Stunting	38071	0.05	0.21
Metabolic Syndrome Index	41919	-0.01	0.50
Hypertension=1	41919	0.25	0.43
Diabetes=1	41919	0.11	0.32
BMI¿30	41919	0.16	0.37
Obesity:WHR=1	41919	0.79	0.40
High Cholestrol=1	41919	0.02	0.15
Chronic Heart Issue=1	41919	0.03	0.17
Chronic Respiratory Issue=1	41919	0.05	0.22
Cancer=1	41919	0.01	0.08
Skin Disease=1	41919	0.05	0.22
Uro-genital Problems=1	41919	0.06	0.23
Neurological Issue=1	41919	0.02	0.14
Grip Strength Deficit	41919	0.40	0.49
Lower Cognitive Score	41919	0.14	0.35

Notes: This table presents summary statisitcs from the LASI. Each row provides the number of observations, mean, standard deviations. The top panel provides demographic characteristics of the individuals born between 1945-1985. The second panel provides the heigth measures of individuals. The third, fourth and fifth panels provide summary of individual level health outcomes.

Table 2: Effect of potential productivity gains on HYV adoption

	Share HYV (W,R)	
	(1)	(2)
ProdGain $\times$ Post^{1965}	0.046***	0.038***
	(0.008)	(0.006)
Observations	13437	13304
Mean of depvar	0.19	0.19
Year and District FE	Yes	Yes
Precipitation & Temperature	No	Yes
Geo. & SE controls x $\mathbf{I}\_t$	No	Yes
Yield controls (W,R)^{1957} x $\mathbf{I}\_t$	No	Yes
Area Share^{1957} x $\mathbf{I}\_t$	No	Yes

Notes: Each column presents the results from estimating equation 1. The dependent variable is the share of area planted using high yielding varieties of wheat and rice in total cultivated area. The sample includes 266 districts in India from 1957 to 2007. Col (1) includes district and year fixed effects. Col (2) includes mean precipitation, temperature, and baseline (1957) controls interacted with year fixed effects: population density, agricultural wages, road density, literacy rate, share of irrigated area, soil Ph, area share of wheat and rice, yield of wheat and rice. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 3: Effect on crop diversity

	Crop Diversity	
	(1)	(2)
ProdGain $\times$ Post^{1965}	-0.093***	-0.087***
	(0.014)	(0.014)
Observations	13566	13413
Mean of depvar	1.50	1.50
Year and District FE	Yes	Yes
Precipitation & Temperature	No	Yes
Geo. & SE controls x $\mathbf{I}\_t$	No	Yes
Yield controls (W,R)^{1957} x $\mathbf{I}\_t$	No	Yes
Area Share^{1957} x $\mathbf{I}\_t$	No	Yes

Notes: Each column presents the results from estimating equation 1. The dependent variable is crop diversity. It is measured using shannon diveristy index=$\sum_{i=1}^{n} p_{i,d,t}\, ln(\frac{1}{p_{i,d,t}})$, where $p_{i,d,t}$ is the area planted under crop i in district d, year t. The data on share of area under each crop comes from district level panel dataset from IACD and ICRISAT. Total 21 crops (cash and consumption crops) are included in the measure accounting for 95% of production in India. The explanatory variable is potential productivity gains (000 kgs/hc) measured from the FAO-Global Agroceconomic Zones v-4 dataset. Col (1) includes district and year fixed effects. Col (2) includes mean precipitation, temperature, and baseline (1957) controls interacted with year fixed effects: population density, agricultural wages, road density, literacy rate, share of irrigated area, soil Ph, area share of wheat and rice, yield of wheat and rice. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 4: Effect on calorie, macro and micronutrient produced per calorie

	Production	Production per calorie							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Calories	Carb.	Protein	Iron	Folate	Zinc	Calcium	Vit B1	Vit B2
ProdGain $\times$ Post^{1965}	29.631***	1.241***	-1.043***	-0.178***	-9.382***	-0.092***	1.046	-0.005	-0.009***
	(6.475)	(0.294)	(0.188)	(0.062)	(2.280)	(0.027)	(3.235)	(0.005)	(0.003)
Observations	13515	13392	13392	13392	13392	13392	13392	13392	13392
Mean of depvar	157.09	200.34	31.16	8.78	102.82	6.29	83.23	0.76	0.37
Year and District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Precipitation & Temperature	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geo. & SE controls x $\mathbf{I}_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yield controls (W,R)^{1957} x $\mathbf{I}_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Share^{1957} x $\mathbf{I}_t$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design by estimating equation 1. Col (1) is total calories produced measured in (000 kcal). Cols (2)-(3) are macronutrients produced per calorie measured in (g/000 kcal). Cols (4), (6)-(8) are iron, zinc, calcium, vitamins per calorie produced measured in (mg/000 kcal). Col (5) measures folate produced per calorie measured in (μg/000 kcal). All columns includes district and year fixed effects, mean yearly precipitation and temperature, and baseline (1957) controls interacted with year fixed effects: population density, agricultural wages, road density, literacy rate and soil Ph. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 5: Cross-sectional relationship between production and consumption per capita

	Consumption per capita (kg/30 days)								
	Wheat	Rice	Maize	FM	Barley	PM	Sorghum	Pigeonpea	Chickpea
Wheat production per capita	0.102***								
	(0.02)								
Rice production per capita		0.166***							
		(0.03)							
Maize production per capita			0.162***						
			(0.03)						
FM production per capita				0.285***					
				(0.03)					
Barley production per capita					0.002				
					(0.00)				
PM production per capita						0.148***			
						(0.04)			
Sorghum production per capita							0.409***		
							(0.03)		
Pigeonpea production per capita								0.065***	
								(0.01)	
Chickpea production per capita									-0.004
									(0.01)
Observations	264	264	264	264	264	264	264	264	264
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column shows estimates from the district level correlation analysis between per capita production of consumption crops and per capita consumption (kg/30 days). The consumption data comes from National Sample Survey: Household Consumption Expenditure, 1999. The household consumption data is aggregated at the district level.. The production data comes from IACD for the year 1999. Each column includes state fixed effects. The crops included are wheat, rice, maize, fingermillet (FM), barley, pearlmillet (PM), sorghum, pigeonpea and chickpea. Robust standard errors are measured and reported in the paranthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 6: Effect of potential productivity gains on height

	Height (cms)	
	(1)	(2)
ProdGain $\times$ Post^{1965}	-0.182**	-0.167**
	(0.073)	(0.074)
Observations	37441	37248
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	No	Yes
Mean of dep. var.	155.685	155.691

Notes: This table presents the results on the effects of potential productivity gains exposure on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 7: Effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.012**	0.000	0.001	0.017***	0.007**	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 8: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.005	0.001	-0.001	0.003
	(0.007)	(0.001)	(0.004)	(0.003)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognititve imbalance index. Cols (2)- (4) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 9: Effect of potential productivity gains on motor skills

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.013	0.007*	-0.001
	(0.010)	(0.004)	(0.003)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are in parentheses and clustered at the district of birth. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 10: Effect of potential productivity gains on agrochemical related health risks

	Agrochemical Health Risk	Components		
	(1)	(2) Respiratory	(3) Urogenital	(4) Cancer
ProdGain $\times$ Post^{1965}	0.0090*	0.0048**	0.0004	0.0003
	(0.005)	(0.002)	(0.002)	(0.001)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	0.002	0.052	0.058	0.006

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for composite measure of agrochemical related health risk. Cols (2)- (5) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 11: Heterogeneity analysis: Effect of potential productivity gains on agrochemical related health risks

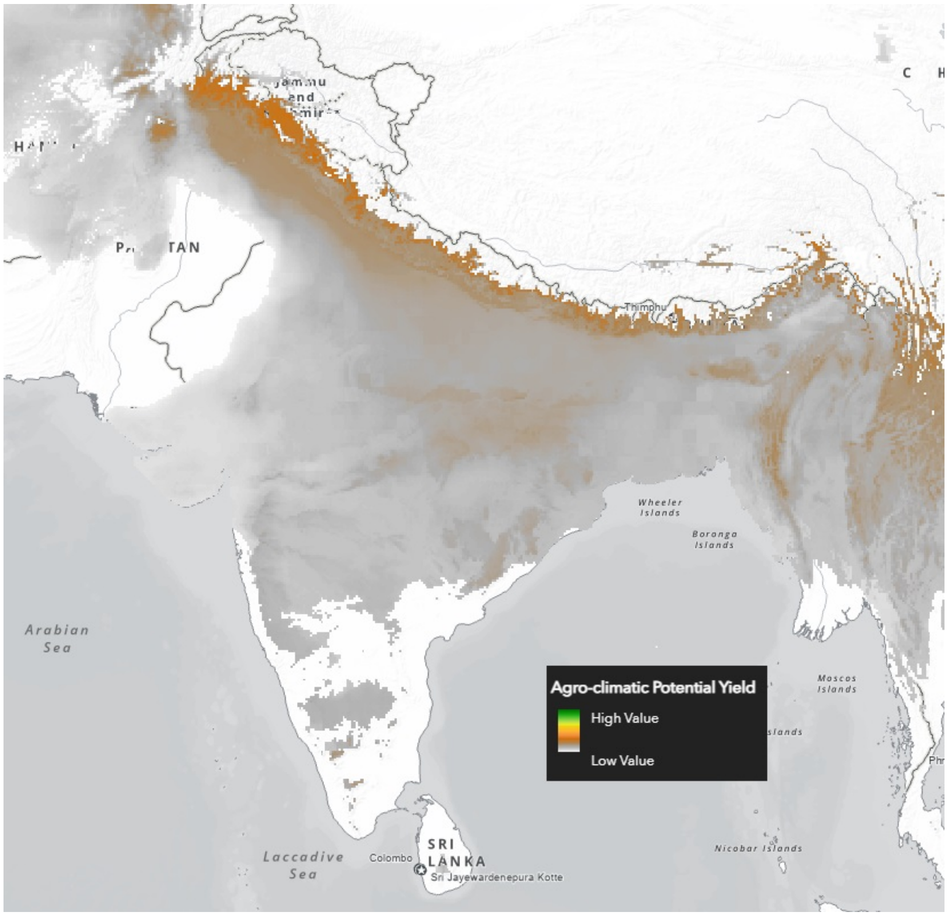
	Agrochemical Health Risk	Components		
	(1)	(2) Respiratory	(3) Urogenital	(4) Cancer
ProdGain $\times$ Post^{1965}	0.0065	0.0037*	0.0003	0.0001
	(0.005)	(0.002)	(0.002)	(0.001)
Rural=1 $\times$ ProdGain $\times$ Post^{1965}	0.0044**	0.0020***	0.0002	0.0003
	(0.002)	(0.001)	(0.001)	(0.000)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	0.002	0.052	0.058	0.006

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for composite measure of agrochemical related health risk. Cols (2)- (5) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

A. Appendix

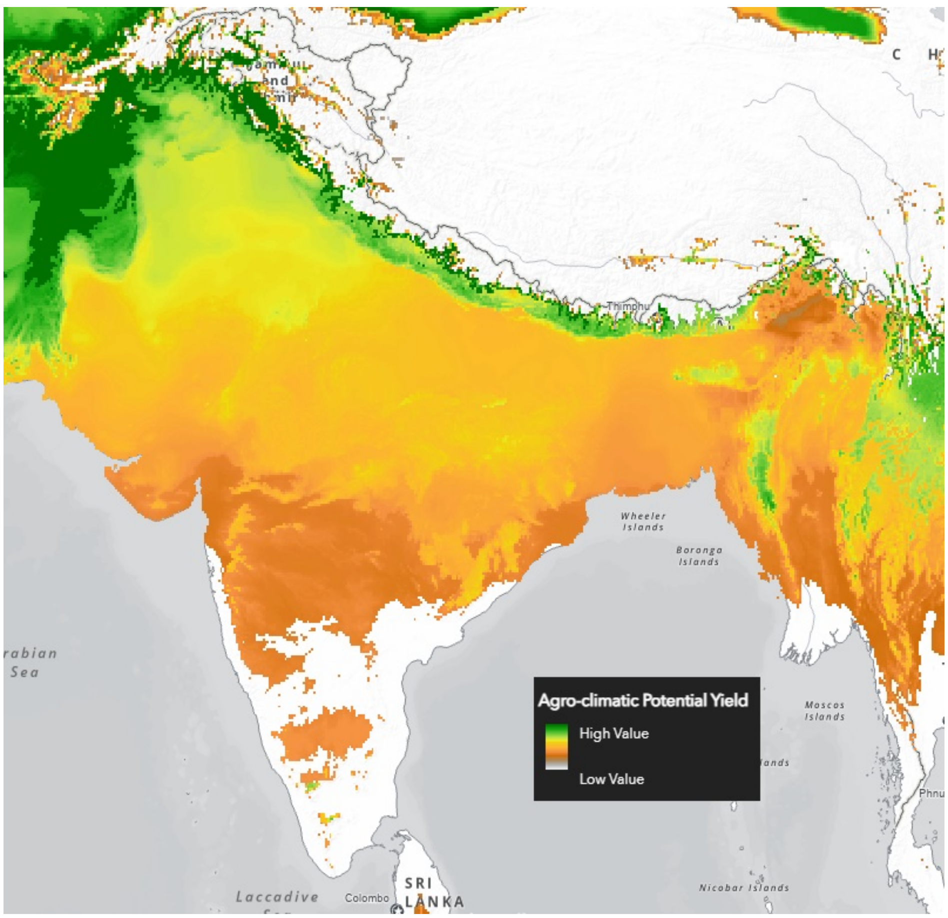
2. Figures

Figure A.1: Potential yield of wheat under low input and rainfed conditions



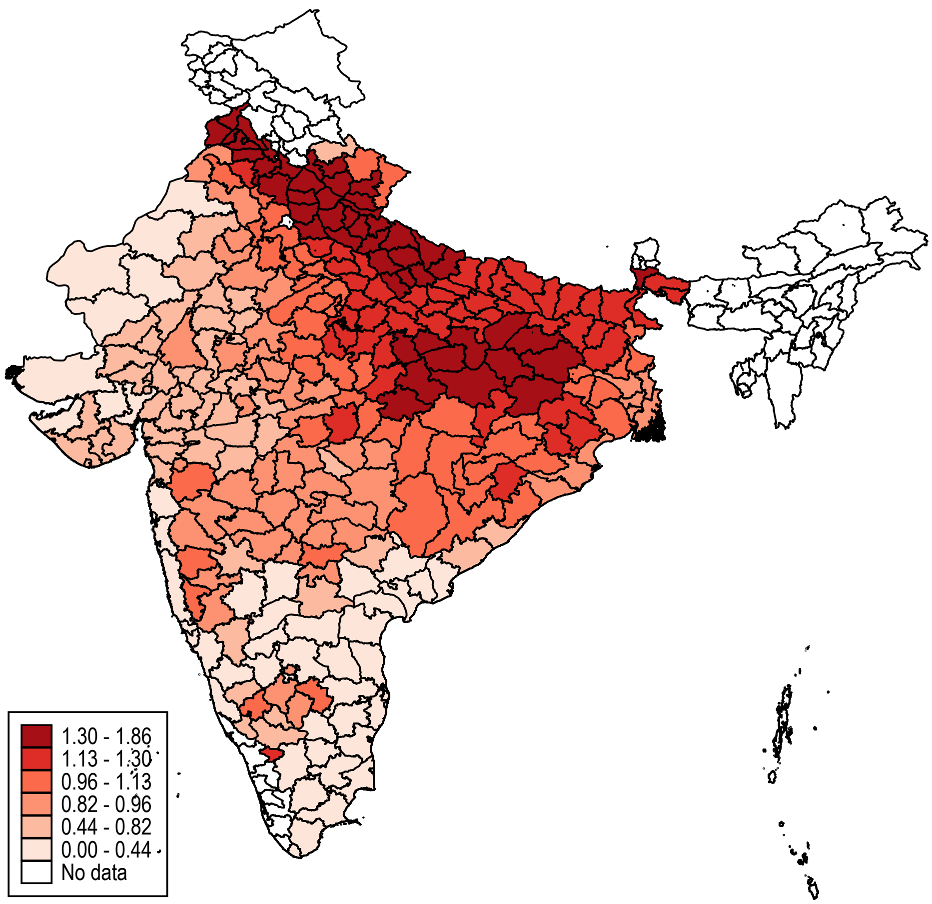
Source: FAO: GAEZ-v4

Figure A.2: Potential yield of wheat under high input and irrigated conditions



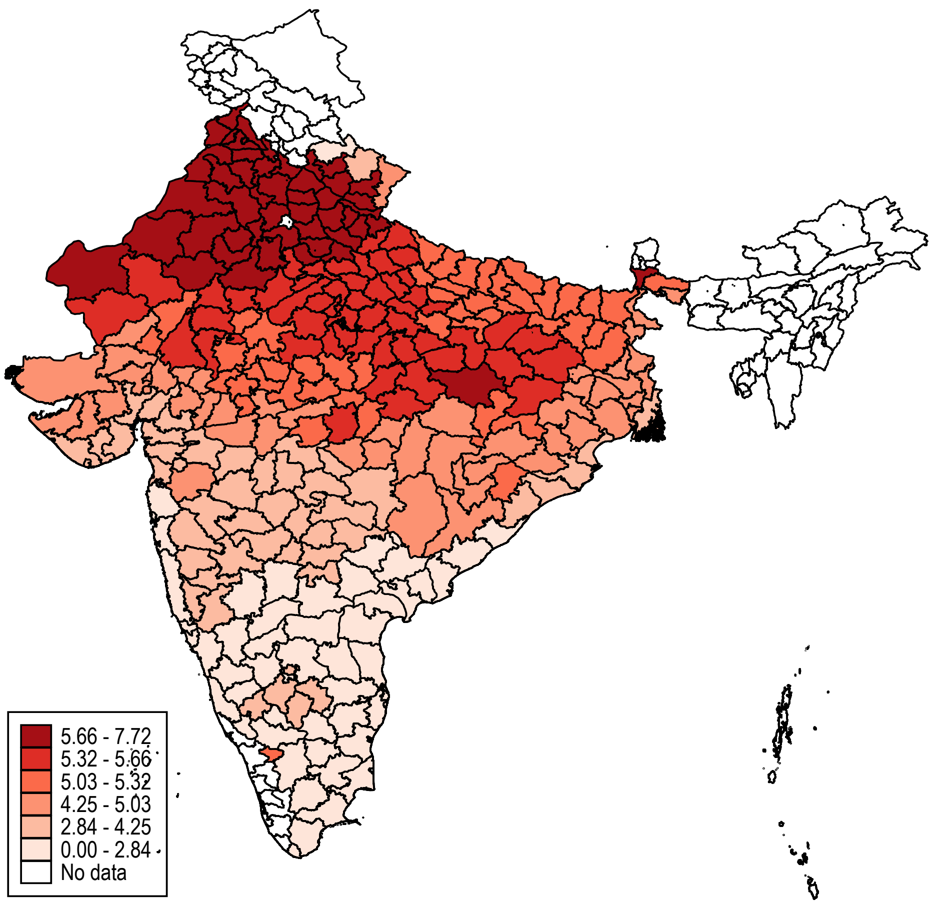
Source: FAO: GAEZ-v4

Figure A.3: Potential yield of wheat under low input and rainfed conditions:



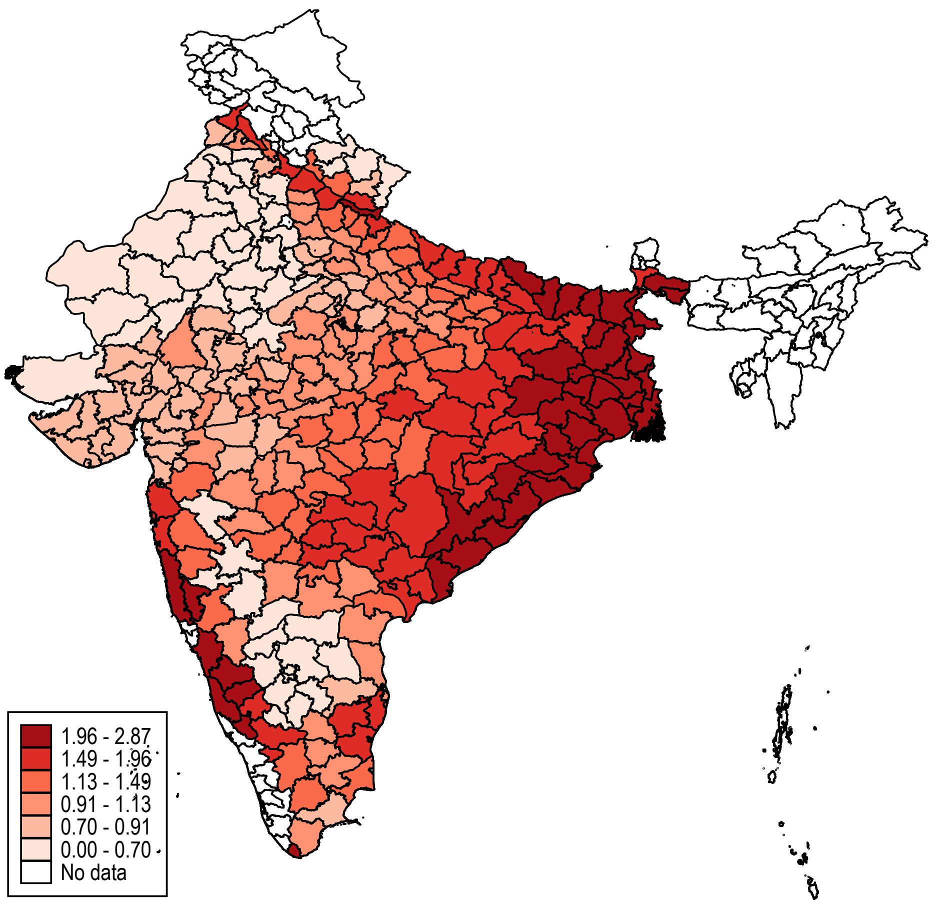
Source: FAO: GAEZ-v4

Figure A.4: Potential yield of wheat under high input and irrigated conditions: Aggregated measures



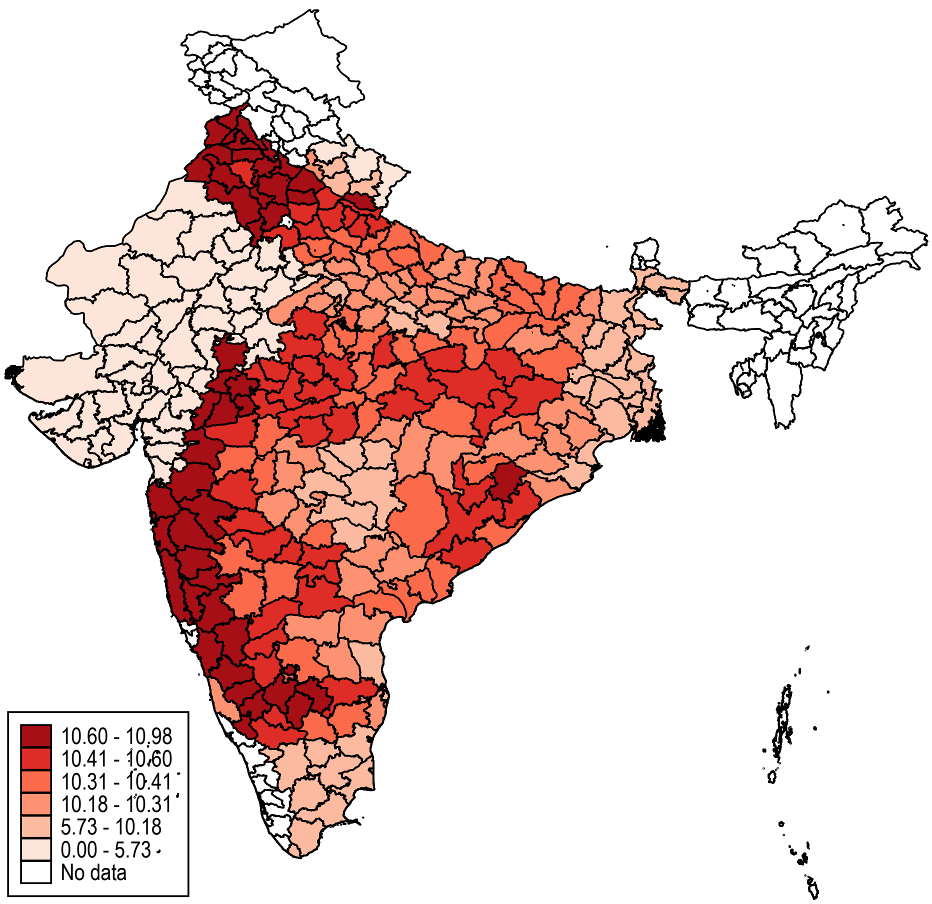
Source: FAO: GAEZ-v4

Figure A.5: Potential yield of rice under low input and rainfed conditions:



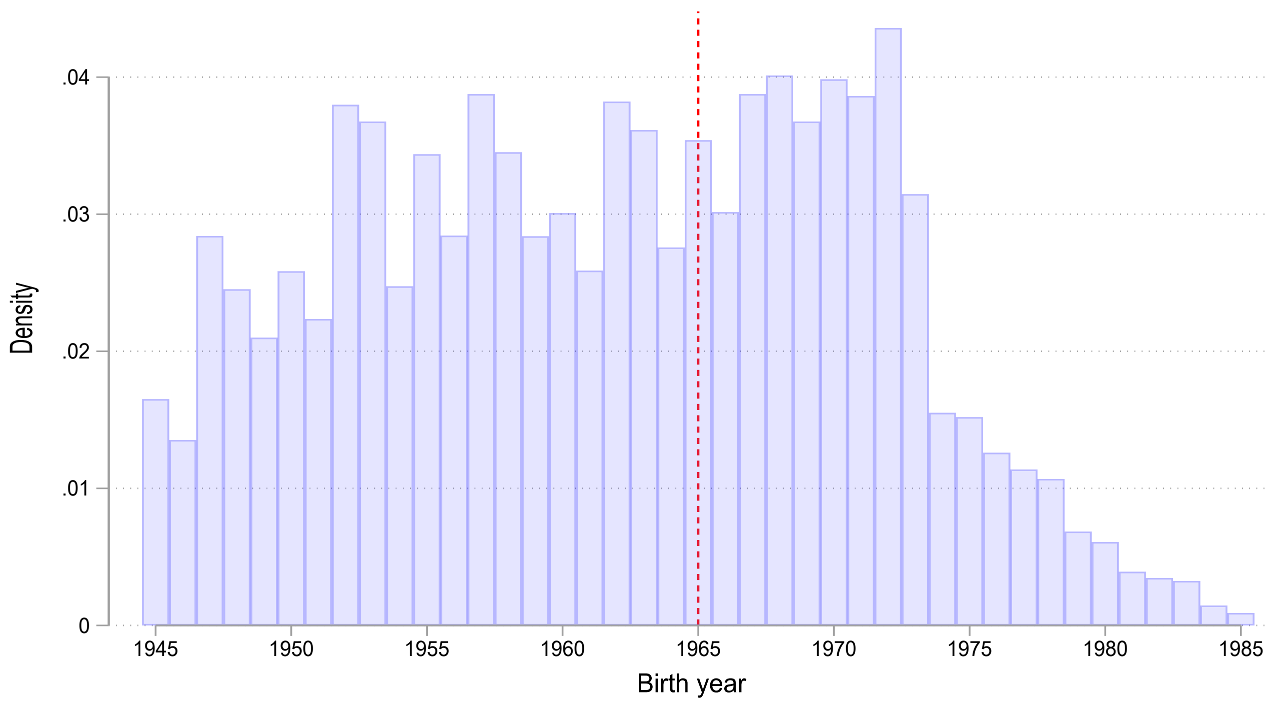
Source: FAO: GAEZ-v4

Figure A.6: Potential yield of rice under high input and irrigated conditions: Aggregated measures



Source: FAO: GAEZ-v4

Figure A.7: Histogram of birth year in LASI sample



Notes: The figure presents a histogram of birth year derived from reported year of birth for those born between 1945 and 1985. The histogram shows that there are no spikes at ages divisible by 5, suggesting that the problem of age-heaping is not present in LASI sample.

Figure A.8: Share of area under wheat in total cultivated area over time

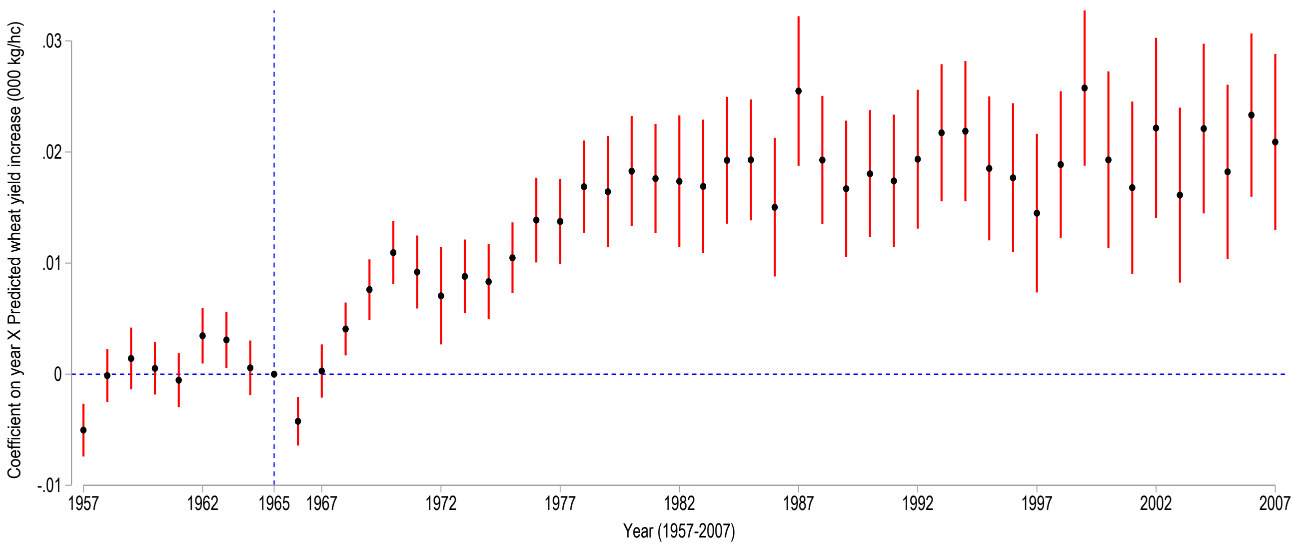
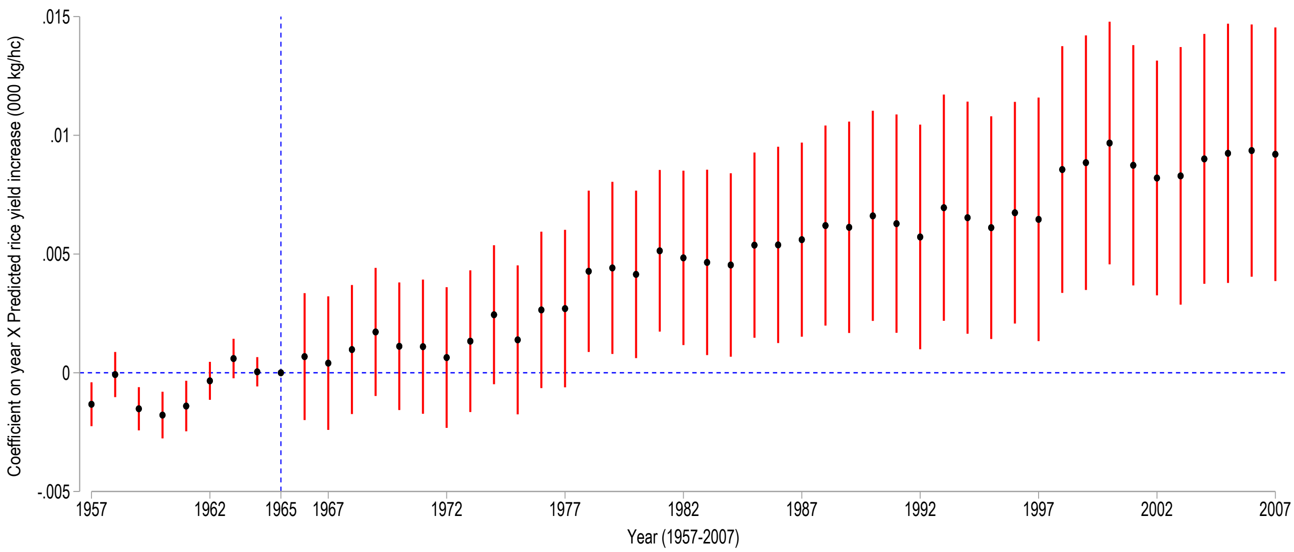
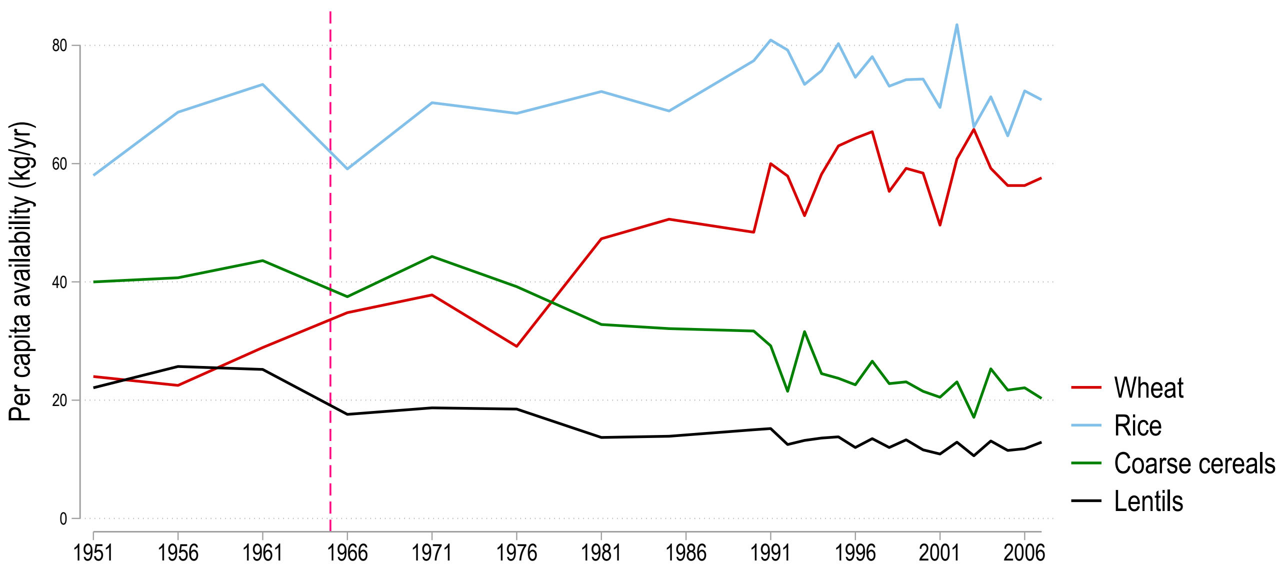


Figure A.9: Share of area under rice in total cultivated area over time



Notes: These figures plot the coefficients from estimating an event-study model using the share of area planted with all high-yield varieties of wheat and rice the dependent variable. The regression includes socio-economic and geographic controls, district and year fixed effects. Vertical bars indicate 95% confidence intervals.

Figure A.10: Trends in per capita availability of food grains



Source: ICRISAT Data

Figure A.11: Event study estimates of vitamin B1 per calorie produced

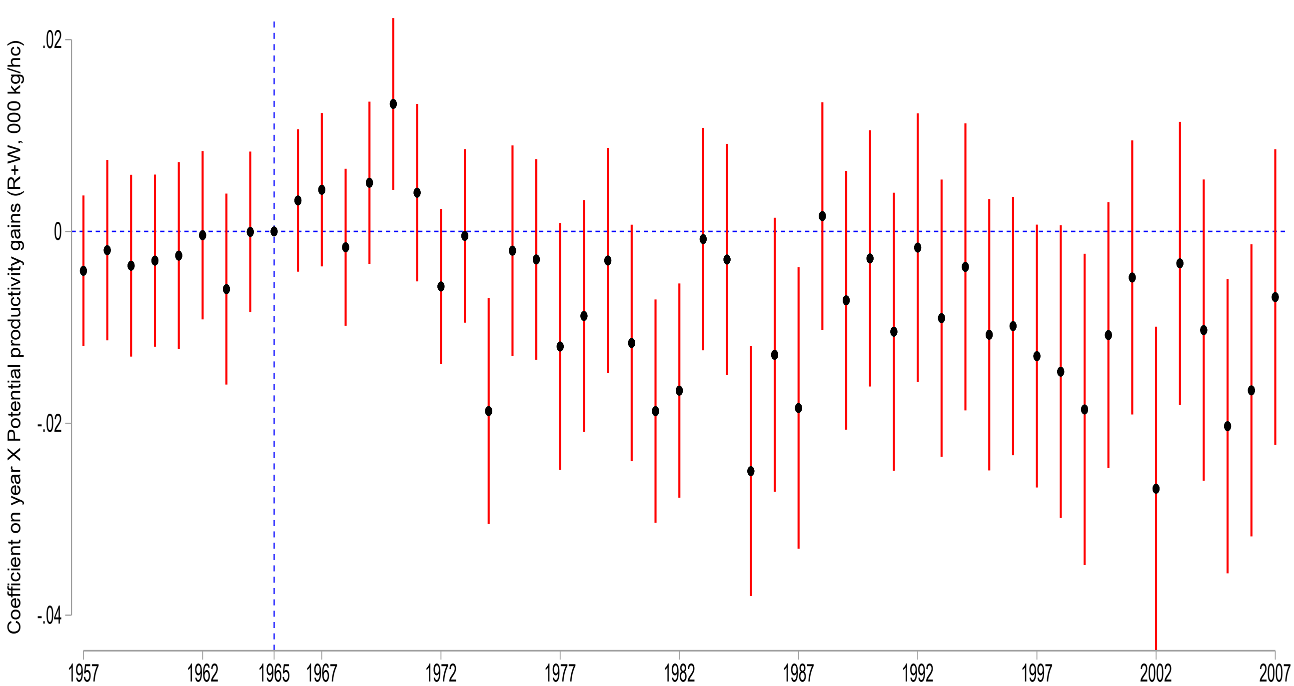


Figure A.12: Event study estimates of vitamin B2 per calorie produced

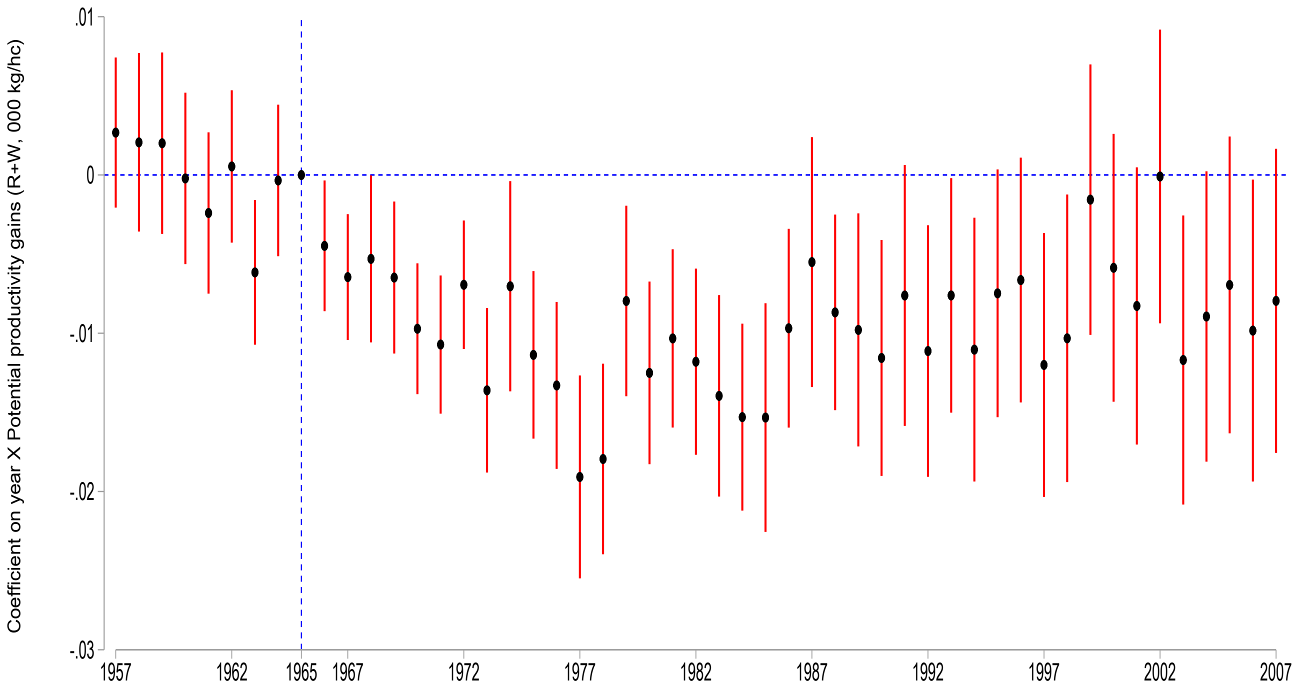
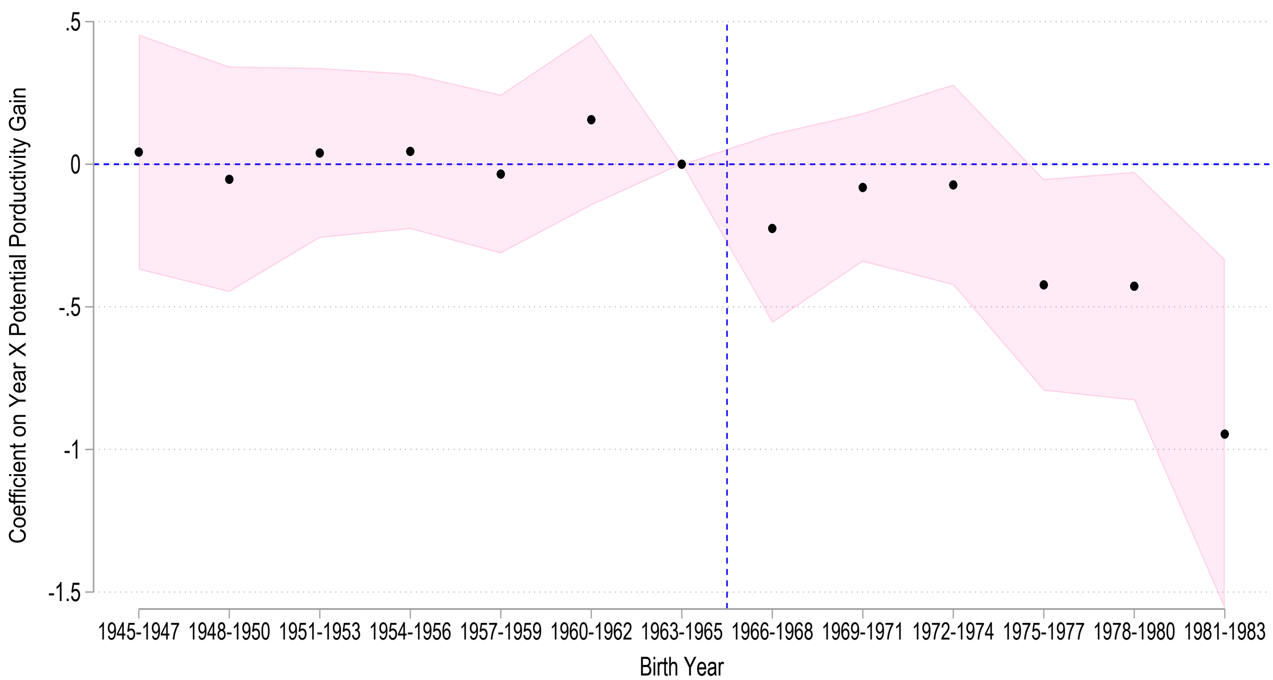
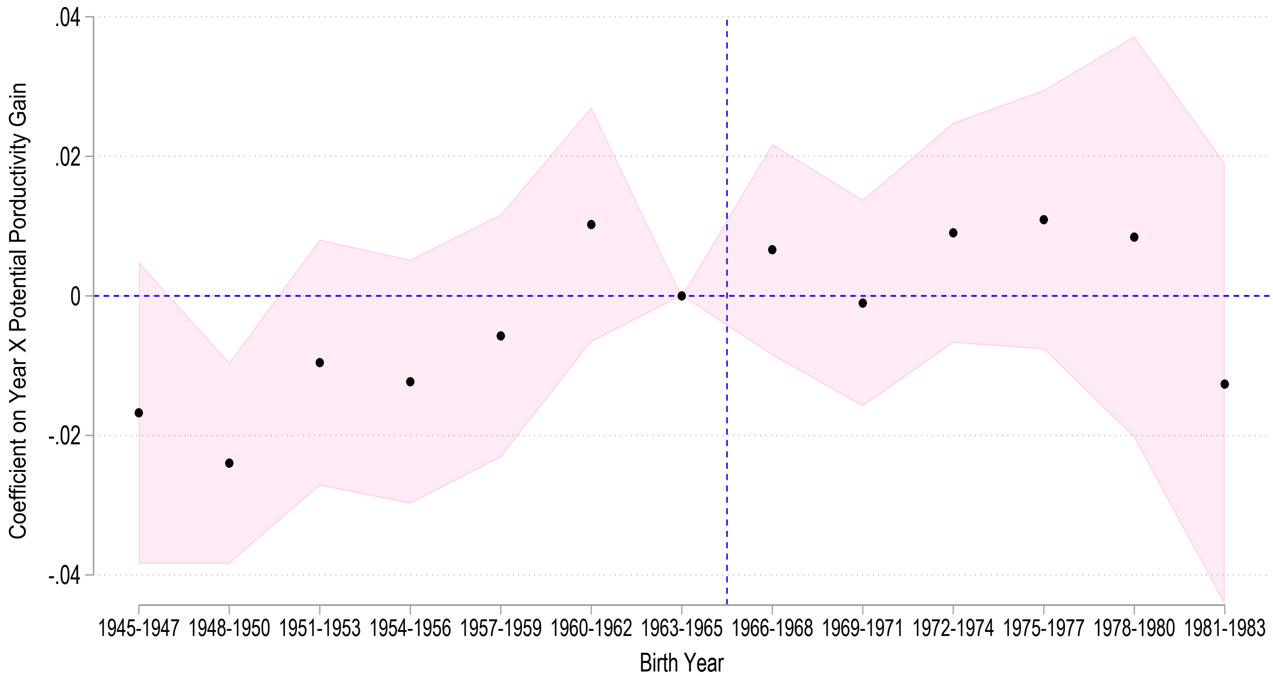


Figure A.13: Event study estimates of the effect of potential productivity gains on height



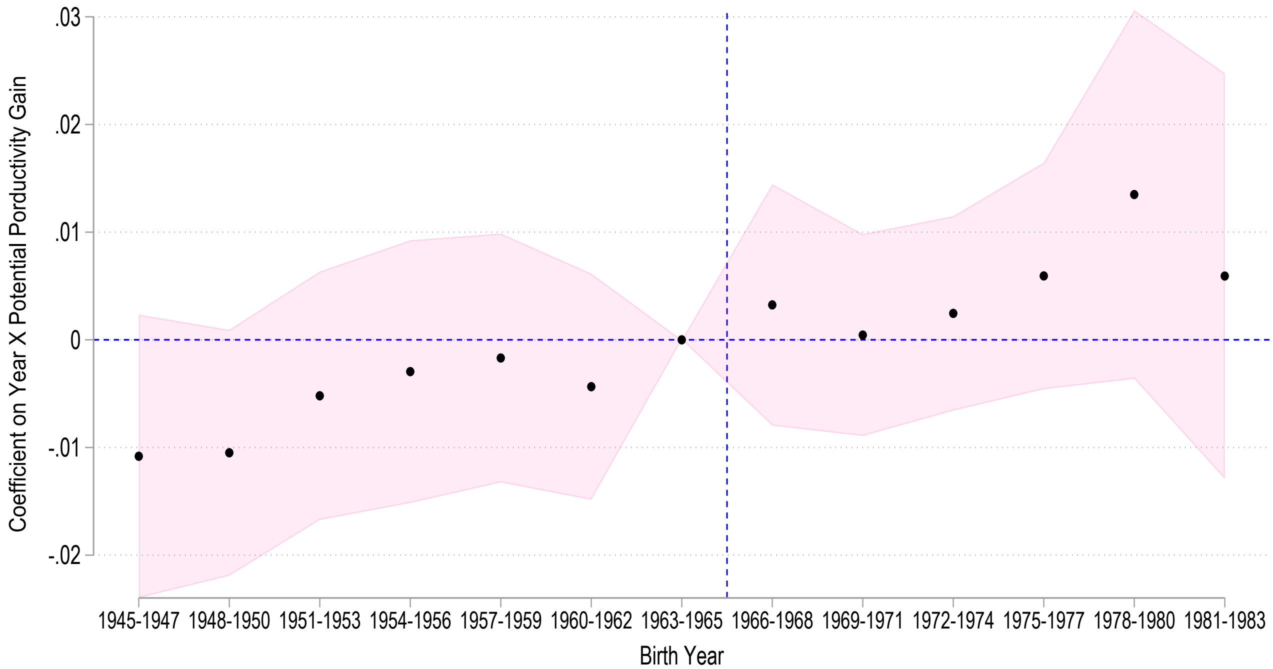
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using height as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

Figure A.14: Event study estimates of the effect of potential productivity gains on metabolic syndrome index



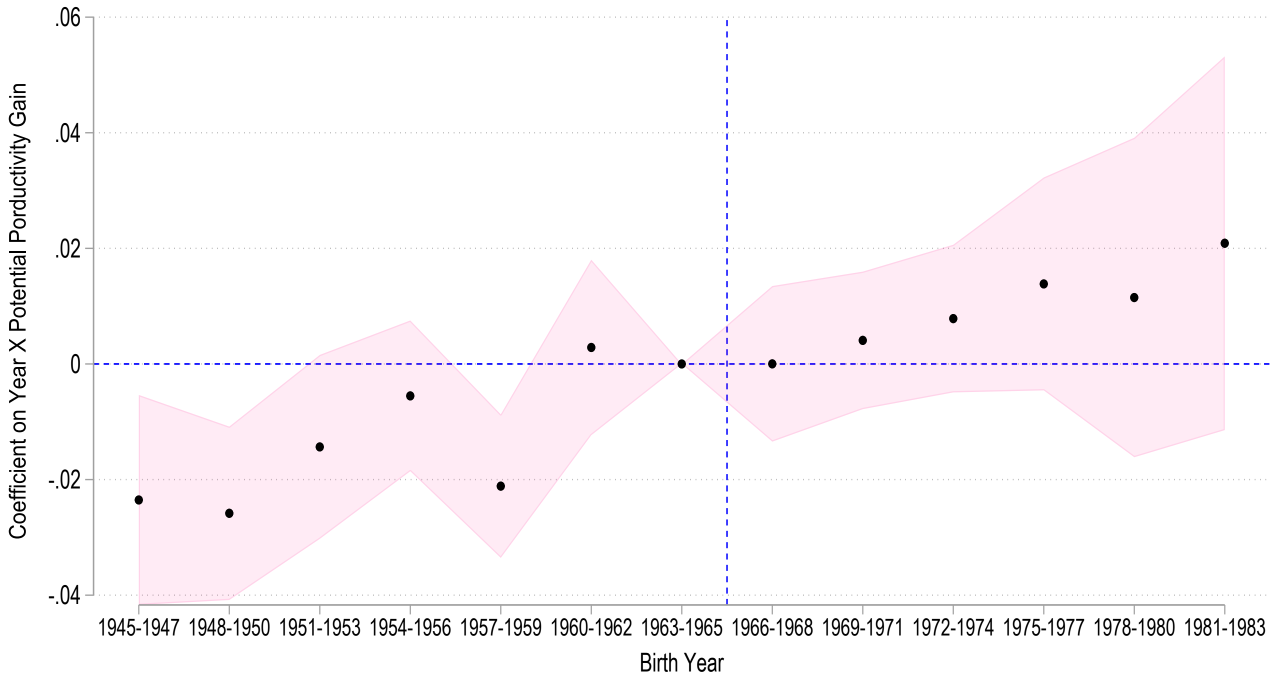
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using metabolic syndrome indexas the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

Figure A.15: Event study estimates of the effect of potential productivity gains on diabetes



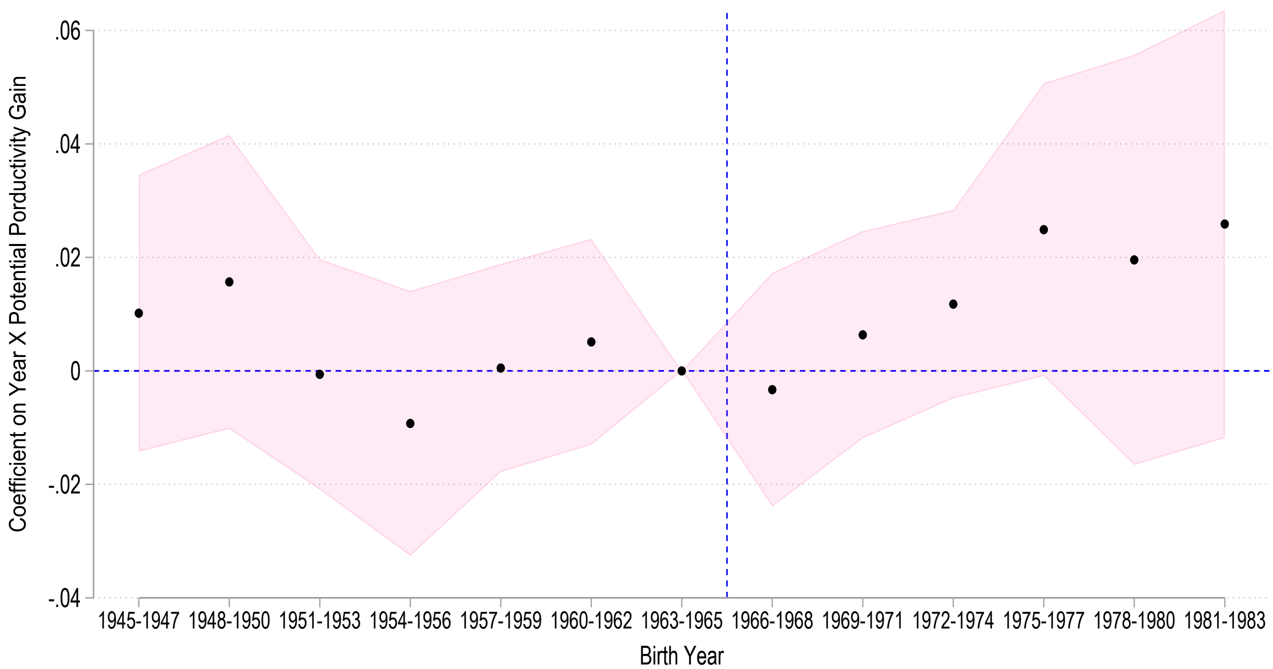
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using diabetes as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

Figure A.16: Event study estimates of the effect of potential productivity gains on hypertension



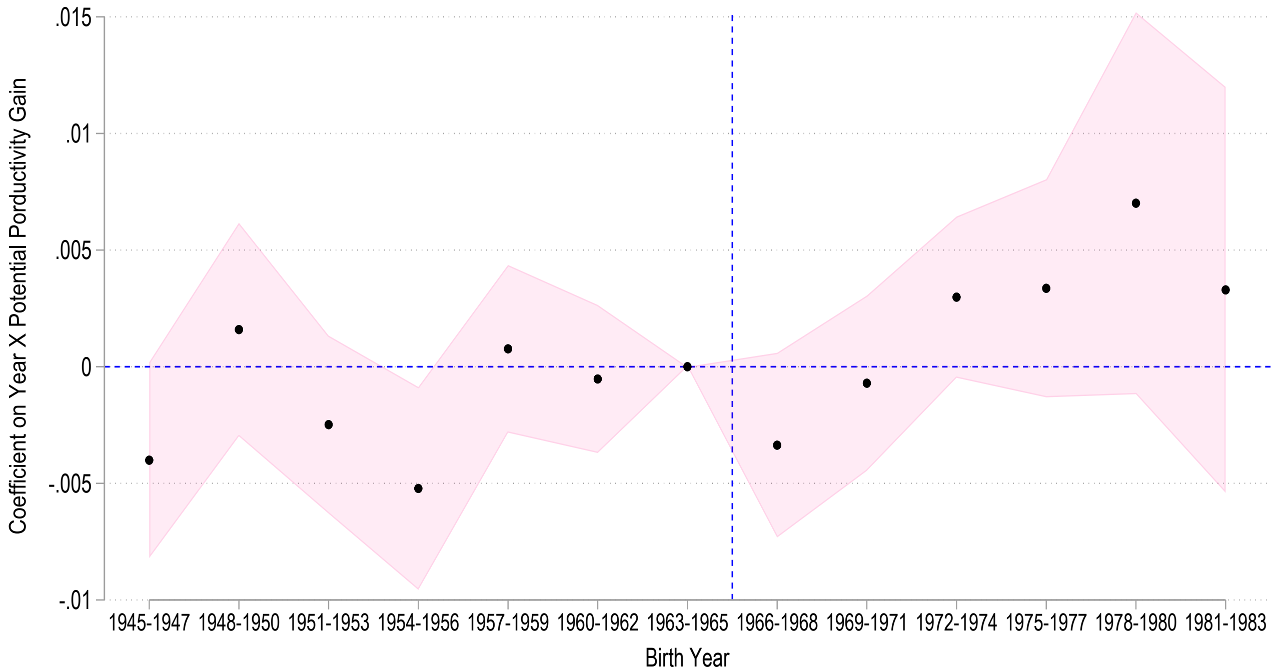
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using hypertension as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

Figure A.17: Event study estimates of the effect of potential productivity gains on cognitive imbalance



Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using cognitive imbalance index as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

Figure A.18: Event study estimates of the effect of potential productivity gains on neurological issues



Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using neurological issues as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at year of birth. Shaded area indicates 90% confidence intervals.

1. Tables

Table A.1: Effect on number of crops

	Number of crops
	(1)
ProdGain $\times$ Post^{1965}	-0.358***
	(0.065)
Observations	13413
Mean of depvar	4.33
Year and District FE	Yes
Precipitation & Temperature	Yes
Geo. & SE controls x $\mathbf{I}_t$	Yes
Yield controls (W,R)^{1957} x $\mathbf{I}_t$	Yes
Area Share^{1957} x $\mathbf{I}_t$	Yes

Notes: Each column presents the results from estimating equation 1. The dependent variable is number of crops. The data on number of crops grown comes from district-level panel dataset IACD and ICRISAT. Total 21 crops (cash and consumption crops) are included in the measure accounting for 95% of production in India. The explanatory variable is potential productivity gains (000 kgs/hc) measured from the FAO-Global Agroceconomic Zones v-4 dataset. Col (1) includes district and year fixed effects. Col (2) includes mean precipitation, temperature, and baseline (1957) controls interacted with year fixed effects: population density, agricultural wages, road density, literacy rate, share of irrigated area, soil Ph, area share of wheat and rice, yield of wheat and rice. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.2: Effect of potential productivity gains on height stunting

	Height Stunting	
	(1)	(2)
ProdGain $\times$ Post^{1965}	0.003	0.003
	(0.002)	(0.002)
Observations	37441	37248
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	No	Yes
Mean of dep. var.	0.048	0.048

Notes: This table presents the results on the effects of exposure to potential productivity gains on height stunting. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.3: Heterogeneity analysis: Effect of potential productivity gains on height

	Height (cms)	
	(1)	(2)
ProdGain $\times$ Post^{1965}	-0.214***	-0.202***
	(0.073)	(0.074)
Female=1 $\times$ ProdGain $\times$ Post^{1965}	0.052**	0.057**
	(0.022)	(0.022)
Observations	37441	37248
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	No	Yes
Mean of dep. var.	155.685	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height stunting. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.4: Heterogeneity analysis: Effect of potential productivity gains on metabolic syndrome

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.011**	0.001	0.003	0.016***	0.007**	-0.002	0.001
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Female=1 $\times$ ProdGain $\times$ Post^{1965}	0.001	-0.000	-0.004**	0.001	-0.000	0.002***	0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.5: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Cognite Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain × Post^{1965}	0.010	0.001	0.001	0.007**
	(0.007)	(0.001)	(0.004)	(0.003)
Female=1 × ProdGain × Post^{1965}	-0.008***	0.000	-0.003**	-0.007***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.6: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.033***	0.013***	0.004
	(0.011)	(0.005)	(0.003)
Female=1 × ProdGain × Post^{1965}	-0.033***	-0.010***	-0.009***
	(0.004)	(0.002)	(0.001)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.7: Heterogeneity analysis: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.170**
	(0.075)
Poor=1 $\times$ ProdGain $\times$ Post^{1965}	0.009
	(0.022)
Observations	37248
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height stunting. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.8: Heterogeneity analysis: Effect of potential productivity gains on metabolic syndrome

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.009*	0.002	0.000	0.013***	0.005	-0.001	0.002
	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Poor=1 $\times$ ProdGain $\times$ Post^{1965}	0.005***	-0.005***	0.002	0.007***	0.006***	0.001**	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.9: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.005	0.002	-0.003	0.004
	(0.007)	(0.001)	(0.004)	(0.003)
Poor=1 $\times$ ProdGain $\times$ Post^{1965}	-0.001	-0.000	0.004**	-0.003**
	(0.002)	(0.000)	(0.002)	(0.001)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.10: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.010	0.006	-0.001
	(0.010)	(0.004)	(0.003)
Poor=1 $\times$ ProdGain $\times$ Post^{1965}	0.007*	0.003**	-0.000
	(0.004)	(0.002)	(0.001)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)-(3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.11: Heterogeneity analysis: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.166**
	(0.075)
Hindu=1 $\times$ ProdGain $\times$ Post^{1965}	-0.002
	(0.027)
Observations	37248
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height stunting. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.12: Heterogeneity analysis: Effect of potential productivity gains on metabolic syndrome

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.011**	0.001	0.003	0.015***	0.007**	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Hindu=1 $\times$ ProdGain $\times$ Post^{1965}	0.001	-0.001	-0.003*	0.003	0.001	0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.13: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.008	0.001	0.001	0.005
	(0.007)	(0.001)	(0.005)	(0.003)
Hindu=1 $\times$ ProdGain $\times$ Post^{1965}	-0.006**	0.000	-0.004*	-0.004**
	(0.003)	(0.001)	(0.002)	(0.002)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.14: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.014	0.008*	-0.002
	(0.010)	(0.004)	(0.003)
Hindu=1 $\times$ ProdGain $\times$ Post^{1965}	-0.000	-0.001	0.001
	(0.004)	(0.002)	(0.001)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.15: Heterogeneity analysis: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.172**
	(0.074)
HEP Months=1 $\times$ ProdGain $\times$ Post^{1965}	0.011
	(0.023)
Observations	37248
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height . HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.16: Heterogeneity analysis: Effect of potential productivity gains on metabolic syndrome

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.012**	0.000	0.001	0.016***	0.008**	-0.001	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
HEP Months=1 $\times$ ProdGain $\times$ Post^{1965}	0.000	0.001	0.001	0.001	-0.001	0.000	-0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.17: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain × Post^{1965}	0.004	0.001	-0.001	0.003
	(0.007)	(0.001)	(0.004)	(0.003)
HEP Months=1 × ProdGain × Post^{1965}	0.002	0.001	0.000	0.000
	(0.002)	(0.000)	(0.002)	(0.001)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.18: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.014	0.008*	-0.001
	(0.010)	(0.004)	(0.003)
HEP Months=1 × ProdGain × Post^{1965}	-0.002	-0.001	-0.000
	(0.004)	(0.002)	(0.001)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.19: Heterogeneity analysis: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.168**
	(0.073)
Observations	37248
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height . HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Columns 1 shows the results with individual controls, district and time fixed effects, and columns 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.20: Heterogeneity analysis: Effect of potential productivity gains on metabolic syndrome

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.012**	0.000	0.001	0.017***	0.007**	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.21: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.005	0.001	-0.001	0.003
	(0.007)	(0.001)	(0.004)	(0.003)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.22: Heterogeneity analysis: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.013	0.007*	-0.001
	(0.010)	(0.004)	(0.003)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. HEP represents the high exposure month based on the sowing months of wheat and rice in India. High exposure months are: October, Novemebr, December, June, July and August. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.23: Effect of potential productivity gains on other health outcomes

	(1) Disaster related issues	(2) Physical injury
ProdGain × Post^{1965}	0.001	-0.002
	(0.001)	(0.003)
Observations	41014	41014
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	Yes	Yes
Mean of dep. var.	0.026	0.121

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are in parentheses and clustered at the district of birth. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.24: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.134
	(0.113)
Observations	37441
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District trends	Yes
Mean of dep. var.	155.685

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects and dsitrict trends. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.25: Effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	-0.006	-0.004	-0.006	-0.004	0.000	-0.002	0.002
	(0.009)	(0.006)	(0.007)	(0.007)	(0.005)	(0.003)	(0.003)
Observations	41229	41229	41229	41229	41229	41229	41229
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.014	0.163	0.794	0.251	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.26: Effect of potential productivity gains on cognitive imbalance

	Cognite Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain × Post^{1965}	0.005	-0.002	0.005	0.006
	(0.010)	(0.002)	(0.007)	(0.004)
Observations	41229	41229	41229	41229
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District trends	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (4) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.27: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.032*	0.015*	0.001
	(0.017)	(0.008)	(0.005)
Observations	41229	41229	41229
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
Mean of dep. var.	-0.028	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (4) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.28: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.150*
	(0.088)
Observations	28035
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.827

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.29: Effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.004	-0.002	-0.000	0.010**	0.002	-0.001	0.001
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)
Observations	30810	30810	30810	30810	30810	30810	30810
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.038	0.168	0.789	0.222	0.097	0.023	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.30: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain × Post^{1965}	0.007	0.000	0.001	0.006*
	(0.007)	(0.001)	(0.005)	(0.003)
Observations	30810	30810	30810	30810
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.043	0.020	0.308	0.124

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (4) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.31: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.015	0.009	-0.002
	(0.012)	(0.005)	(0.003)
Observations	30810	30810	30810
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.081	0.391	0.127

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.32: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.370***
	(0.134)
Observations	16345
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.804

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.33: Effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.002	-0.008	0.006	0.014**	-0.002	-0.000	-0.001
	(0.009)	(0.006)	(0.006)	(0.007)	(0.005)	(0.003)	(0.003)
Observations	18023	18023	18023	18023	18023	18023	18023
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.036	0.169	0.787	0.228	0.093	0.023	0.024

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.34: Effect of potential productivity gains on cognitive imbalance

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.015	-0.000	0.008	0.010***
	(0.010)	(0.003)	(0.006)	(0.004)
Observations	18023	18023	18023	18023
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.044	0.021	0.310	0.121

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (4) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.35: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.041**	0.016**	0.005
	(0.017)	(0.007)	(0.006)
Observations	18023	18023	18023
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.062	0.396	0.132

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.36: Rural-urban heterogeneity analysis: effect of potential productivity gains on height

	Height (cms)	
	(1)	(2)
ProdGain $\times$ Post^{1965}	-0.208***	-0.193***
	(0.073)	(0.074)
Born in rural area=1 $\times$ ProdGain $\times$ Post^{1965}	0.044*	0.043*
	(0.024)	(0.024)
Observations	37441	37248
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	No	Yes
Mean of dep. var.	155.685	155.691

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.37: Rural-urban heterogeneity analysis: effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.013**	0.002	0.004	0.017***	0.007*	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)	(0.001)
Born in rural area=1 $\times$ ProdGain $\times$ Post^{1965}	-0.002	-0.002	-0.004***	0.001	0.000	0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	41229	41229	41229	41229	41229	41229	41229
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.014	0.163	0.794	0.251	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.38: Rural-urban heterogeneity analysis: effect of potential productivity gains on cognitive imbalance

	Cognite Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain $\times$ Post^{1965}	0.010	0.002	-0.001	0.006*
	(0.007)	(0.001)	(0.004)	(0.003)
Born in rural area=1 $\times$ ProdGain $\times$ Post^{1965}	-0.007***	-0.001	-0.001	-0.005***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	41229	41229	41229	41229
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (4) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.39: Rural-urban heterogeneity analysis: effect of potential productivity gains on motor deficit

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.037**	0.016*	0.004
	(0.017)	(0.008)	(0.005)
Born in rural area=1 $\times$ ProdGain $\times$ Post^{1965}	-0.010***	-0.002	-0.004***
	(0.004)	(0.002)	(0.001)
Observations	41229	41229	41229
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District trends	Yes	Yes	Yes
Mean of dep. var.	-0.028	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different cognitive outcomes. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.40: Effect of potential productivity gains on height

	Height (cms)	
	(1)	(2)
ProdGain	-0.322***	-0.328***
	(0.098)	(0.095)
Observations	37441	37248
Indv. controls	Yes	Yes
District FE	Yes	Yes
YOB FE	Yes	Yes
District controls	No	Yes
Mean of dep. var.	155.685	155.691

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.41: Effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain	0.016***	-0.008	-0.002	0.031***	0.013***	0.002	0.000
	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.42: Effect of potential productivity gains on cognitive imbalance

	Cognite Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain	0.023***	0.005***	0.008	0.005
	(0.008)	(0.002)	(0.006)	(0.004)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.43: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain	0.040***	0.018***	0.002
	(0.012)	(0.005)	(0.005)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district and time fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.