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 and agrochemicals introduced 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 also observe a higher incidence of non-diet-related chronic respiratory conditions among those born in rural areas exposed to agrochemicals during early childhood. I conclude that early childhood adverse nutritional changes and agrochemical exposure 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, respiratory disorders, and cancer [Siddique et al., 2021, Meenakshi, 2016, Pingali et al., 2017, Thow et al., 2016]. Qualitative studies suggest that nutritional changes and environmental contaminants 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 through the use of synthetic pesticides and fertilizers, 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, potentially contributing to health issues associated with dietary shifts and raising concerns about the long-term impacts of agrochemical exposure [Shiva, 1991, Pingali et al., 2017, 2019]. Despite these anecdotal accounts, systematic empirical evidence on the Green Revolution's effect on long-run health outcomes is scarce. Studying these outcomes is challenging due to limited data on individuals born before and after its onset, making it difficult to analyze either the adverse health effects related to nutritional access or those associated with agrochemical exposure.

In this paper, I address this gap by tracing the causal chain from the Green Revolution to crop diversity, nutritional shifts, and examining health outcomes associated with dietary and non-dietary factors. First, I show that Green Revolution technologies contribute to reduced crop diversity, particularly affecting lentil and millet production. Next, I provide evidence that while caloric availability has increased, protein and micronutrient access has declined. Finally, I find that individuals exposed to the Green Revolution in early childhood tend to be shorter, exhibit higher rates of metabolic syndrome, and display deficits in motor function, likely due to diminished nutritional access. Additionally, I observe a greater incidence of non-diet-related chronic respiratory conditions among those born in rural areas potentially exposed to agrochemicals during early childhood.

To establish causality, I use a difference-in-differences (DiD) framework, leveraging two sources variations: the timing of Green Revolution's introduction in 1966 and cross-district differences in potential productivity gains of wheat and rice based on climatic and ecological conditions. The intuition is that climatic conditions favorable for wheat and rice production influence the uptake of Green Rev-

[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].

olution technologies. Regions with higher potential productivity gains from HYVs are more likely to shift from traditional varieties to these technologies. This identification strategy is based on empirical work in economic development and history that utilizes variations in ecological and geographic characteristics as exogenous factors influencing technology adoption [Nunn and Qian, 2011, Bustos et al., 2016, Bartik et al., 2019, Moscona, 2023]. For the potential productivity gains, I use potential yield (kg per hectares) models provided by the Food and Agriculture Organization (FAO). These models estimate maximum potential crop yields of wheat and rice at a high resolution grid cell-level, considering climatic suitability and do not rely on a statistical analysis of production patterns observed in India. They provide two yield estimates for each crop per grid cell: one with traditional practices and another with modern technologies (HYVs). I aggregate these to the district level to create a district-specific measure of potential productivity gains for wheat and rice.

I start by providing evidence that districts with higher potential productivity gains from wheat and rice have higher HYV adoption rates.[2] To do this, I use a longitudinal dataset with annual district-level data on HYV wheat and rice areas, total cropped area, and production for 21 crops across 266 districts from 1957 to 2007. Next, I assess the impact of potential productivity gains on crop diversity, showing a decrease from an average of 5 crops to 2.5 crops in districts with the highest gains.[3] I perform an event study analysis that confirms the parallel trends assumption. The results are consistent across different measures of crop diversity. The decline in crop diversity is driven by the reduced area of barley, pearl millet, chickpea, pigeonpea, minor pulses, and groundnut, along with a decline in their production.

The reduction in crop diversity may reduce the availability of nutrients that are important for health.[4] To explore this, I translate crop production data into caloric and nutrient equivalents using National Food Composition Table (2017) to evaluate the effects on total calorie production and nutrient supply per calorie. Exposure to HYV increases calorie production by 20% and raises carbohydrate supply per calorie by 0.6%. However, protein supply per calorie declines by 3%. Additionally, iron decreases by 2%, folate by 9%, and zinc by 2%.

This could affect nutritional intake, particularly in India, where limited market integration and high price dispersion persist [Chatterjee and Kapur, 2017]. Increased wheat and rice production may have lowered prices for these staples in some districts compared to others, leading to greater consumption of these grains. Moreover, even with increased incomes and a demand for dietary diversity, the supply of diverse crops may not be keeping up, as their overall production continues to decline.[5]

After establishing the changes in caloric and nutrient availability, I examine how these nutritional shifts affect health outcomes. Using a similar empirical design, I analyze whether cohorts born just before and after the Green Revolution show persistent differences in health outcomes. By comparing

[2] HYV adoption rate is defined as the share of land under HYV wheat and rice in total cropped area. I control for district, time fixed effects and district-time varying factors: precipitation and temperature, and baseline district characteristics, including crop areas, yields of wheat and rice, and socio-economic variables, interacted with year fixed effects

[3] Crop diversity is defined using Shannon Diversity Index. For more details, see Section 3.1

[4] India's food supply is predominantly plant-based, with plant foods contributing around 94% of total food energy, micronutrients and 85% of total protein [Hopper, 1999]

[5] Pingali et al. [2019], Pingali [2012] highlights that while the Green Revolution effectively solved calorie sufficiency, it led to reduced dietary diversity and failed to address micronutrient deficiencies, "hidden hunger", and dietary quality.

individuals born in affected districts 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. [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]. [6]

I use individual-level nationally representative data from the 2017 Longitudinal Aging Study in India (LASI) for individuals born between 1945 and 1985. The dataset records district of birth, enabling me to link health outcomes to birth districts and account for non-random migration. 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 0.2 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 0.014 standard deviation rise in metabolic syndrome, driven by a 2 percentage point increase in hypertension and a 0.8 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 diet-related 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 pesticide exposure. While I include fertilizer exposure at birth in my preferred specification, pesticide exposure remains a concern due to adoption practices, with rural populations likely more exposed to pesticides. 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. The improvement in calorie availability in rural areas from the Green Revolution likely offset some of the the negative effects of lower protein and micronutrient intake. Additionally, there are no significant differences in metabolic syndrome, cognitive imbalance, or motor deficits between rural and urban births. I also eliminate the possibility of composition effects that could arise if the Green Revolution influenced the types of individuals who survived and experienced adverse health outcomes.

Lastly, I examine the effects of exposure to Green Revolution technologies on non-diet-related

[6] 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].

health outcomes- chronic respiratory disorders and cancer, potentially influenced by agrochemical exposure. My findings show a statistically significant effect on chronic respiratory disorders, stronger among individuals born in rural areas.[7, 8] I rule out other potential mechanisms, specifically exposure to heavy pesticide-using crops like cotton and sugarcane, as well as crop residue burning.

My research sheds light on the long-term, unanticipated health impacts of the Green Revolution in India, underscoring its relevance to the current discourse on Green Revolution 2.0. This modern approach emphasizes sustainable agricultural practices aligned with Sustainable Development Goals of zero hunger and responsible consumption and production. This study emphasizes the significance of improving crop diversity and nutrition, along with the responsible use of chemical inputs, to enhance health outcomes.

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. My study expands on existing research by providing a comprehensive analysis of an extensive range of long-run health outcomes related to the Green Revolution. My central contribution lies in a detailed analysis of the long-term effects on nutrient availability—particularly declines in protein, iron, zinc, and folate—and evidence of health effects that extend beyond nutrition, including those related to agrochemical exposure.

Second, this study also contributes to the growing research on the health effects of environmental contamination [Chay and Greenstone, 2005, Currie and Neidell, 2005, Dias et al., 2023, Calzada et al., 2023]. My use of ecological suitability for HYV wheat and rice, along with the introduction of the Green Revolution in 1966, parallels Maertens [2017], who found that increased pesticide use in corn fields led to higher rates of fetal malformations and perinatal deaths. To the best of my knowledge, this is the first study to document the long-term effects of potential agrochemical exposure in early childhood on chronic respiratory disorders.[9]

Third, my paper contributes to the broader literature on how economic and nutritional resources

[7] For comprehensive review on the effects of pesticides on reporductive health, cancer and uro-genital issues, please refer to Hallenbeck and Cunningham-Burns [2012]

[8] Medical evidence linking low maternal protein diets to respiratory disorders or cancer risk is limited. Key micronutrients essential for the development of pulmonary function—Vitamins A and D—are not sufficiently provided by millets, pulses, rice, or wheat, indicating that nutritional shifts are unlikely to contribute to respiratory issues [Christian and Stewart, 2010].

[9] Another study by Fletcher and Noghanibehambari [2024] examines in-utero pesticide exposure, revealing that males born in top-quartile tree-crop counties and exposed to a cicada event during fetal development have shorter lifespans.

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.

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 Effects of Adoption of HYV Wheat and Rice

The Green Revolution's surge in wheat and rice productivity raised farmers' incomes, potentially influencing long-term health through changes in diet. If wheat and rice are considered normal goods, an increase in income would likely boost their consumption. This effect might be compounded by the relative price reductions due to greater supply [Pingali, 2019]. As mentioned earlier, markets were likely not fully integrated, local production changes had a stronger impact on local prices, leading to higher consumption of wheat and rice compared to other foods due to increased income and lower prices.[10], [11] On the other hand, rising incomes could encourage dietary diversification, but this depends on the availability of diverse foods. The focus on HYVs of wheat and rice likely reduced millet and lentil production, limiting crop diversity. With little technological advancement or market support for these crops, supply constraints may have restricted their availability despite growing demand for varied diets. [Pretty and Bharucha, 2014, Pingali, 2019].

Wheat and rice provide essential calories but differ significantly in nutritional value compared to millets and pulses. Wheat contains 12-15% protein, rice about 7-8%, while pulses are richer at 20-25%. Pulses also have a superior amino acid profile, offering 45 mg of essential amino acids per gram, compared to rice's 16.5 mg and wheat's 9.5 mg. Although rice outperforms wheat in amino acids, both grains are inferior to pulses. Additionally, millets and pulses are high in essential micronutrients like iron, calcium, folate, and zinc, while polished wheat and rice are lower in these nutrients.[12]

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,

[10] 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)

[11] 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].

[12] Most Indians have a diet consisting of a cereal, pulses (often as a soup), or a curried vegetable, typically eaten twice a day [Hopper, 1999].

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.

In addition to potential nutritional changes, the Green Revolution significantly increased agrochemical usage. The adoption of HYV wheat and rice led to a dramatic rise in pesticide use, which grew from 16 grams per hectare in the 1950s to 390 grams per hectare by the 1990s. Similarly, chemical fertilizer application surged from 0.5 kilograms per hectare to 65 kilograms per hectare during this period. [Chand and Birthal, 1997]. The Government of India heavily subsidizes these pesticides and fertilizers, and recent research indicates that these substantial subsidies are a key factor in their overuse.[13] Agrochemical exposure can happens through direct contact with crops, inhalation during spraying, or consuming contaminated food and water. While rural communities face higher risks due to proximity, urban areas are also impacted as pesticides can drift through air and contaminate soil, water, and food, posing long-term health risks. The pattern of pesticide usage in India is different from that for the world in general. In India 76% of the pesticide used is insecticide, as against 44% globally (Mathur, 1999). The use of herbicides and fungicides is correspondingly less heavy. The two most important crops for which pesticides are used after cotton are rice and wheat. organochlorine (OC) insecticides, used successfully in controlling a number of diseases, such as malaria, and typhus, were banned or restricted after the 1960s in most of the technologically advanced countries. The introduction of other synthetic insecticides, i.e., organophosphate (OP) insecticides in the 1960s, carbamates in 1970s, and pyrethroids in 1980s, and the introduction of herbicides and fungicides in 1970s–1980s contributed greatly in pest control and agricultural output. The most important class of insecticides used in India is the organophosphates (OPs), whic

Given these insights into dietary shifts and increased agrochemical usage, there could be profound effects on long-term health outcomes. I will focus on how the influence of nutritional changes and agrochemicals in-utero and early childhood—affected by maternal dietary patterns and exposure—might have lasting impacts on health.

2.3 Prior Evidence on Health Effects of In-Utero Nutritional and Environmental 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

[13] See [Roy et al., 2009] for reference.

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 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).

Environmental Exposure

In environmental health, the adverse health effects observed in children whose mothers used the drug diethylstilbestrol (DES) during pregnancy serve as a pivotal example of the "developmental origins of adult disease" hypothesis. DES resulted in cancer and other adverse reproductive health outcomes in the daughters and sons of women who took the drug while pregnant, and these health impacts emerged only decades after the in utero exposure occurred. Just as nutrients are transferable between mother and fetus, so are chemical contaminants. Studies find pesticide compounds present in the mother's blood can transfer to the fetus via the umbilical cord. Many pesticides can cross the placental barrier, entering the fetal circulation. The extent of transfer depends on the pesticide's chemical properties and molecular size [Rager et al., 2020].

In India, insecticides account for major share of pesticide application. The most common class of insecticides is organophosphates (OPs) [Barathi et al., 2023]. Exposure to (OPs) can harm respiratory health, particularly when it occurs in utero. Research indicates that even low levels of OPs can affect respiratory health, with in utero and early life exposures increasing the risk of childhood asthma.

Add Deaton on height

The fetal origins hypothesis also posits that adverse nutrition conditions during fetal development can have long-lasting impacts on an individual's cognitive function. seminal work also highlighted the link between poor prenatal nutrition and cognitive deficits. Medical literature suggests that fetal malnutrition can affect brain development, leading to reduced cognitive abilities and an increased risk of neuropsychiatric disorders [Martorell, 2017]. 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] . These findings underscore the critical importance of optimal prenatal nutrition and health in preventing cognitive impairments and enhancing long-term cognitive outcomes.

3. Data

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):

These sources provide district-level annual data on the area planted to HYV for wheat and rice,[14] total area cropped under each crop (in hectares) 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 in India from 1957 to 2007. Apart from the data on agricultural outcomes, the dataset also has information on socioeconomic, climatic, edaphic, 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. add figures on HYV area under wheat and rice

To compute the main explanatory variable, 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].[15] Appendix Figures **??** and 2 show the average district-level HYV adoption and crop diversity between the time period 1960-2007.

3.2 Potential Yield of Wheat and Rice

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

To estimate the effect of adoption of HYV wheat and rice, I develop a metric for potential productivity gains, based on the idea that Green Revolution technologies and HYV seeds for wheat and rice are more likely to be adopted in districts with greater potential productivity gains from their adoption. 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

[14] It also has information on area planted under HYV maize, sorghum and pearl millet

[15] 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.

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 predicted productivity gains metric is then calculated as the difference between the potential yields of wheat and rice under high-input,irrigated conditions and low-input, rainfed conditions.[16] 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.[17] [18]

3.3 Individual Health Outcomes

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

LASI is a nationally representative survey of individuals aged above 45 years and including their spouses (including less than 45 years). It comprises of 42000 individuals born between 1945-1985 from the above mentioned 13 states. The data is sampled from 2440 villages and towns according to 2011 census. It provides information on demographics, household economic status, chronic health conditions, symptom-based health conditions, functional health, mental health (cognition and depression), biomarkers, work and employment, satisfaction, and life expectations, childhood health, family medical history. The data also includes information on "district of birth" & "years where spent most of the childhood". I match the IACD data with the LASI data based on the district of birth rather than district of residence to rule out non-random migration. After the matching, I get individual level health

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

[17]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]

[18]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.

outcomes for people born in 251 districts[19] ,[20]

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, (iv) self-reported incidence of chronic respiratory disease, urogenital problems and cancer. I create two measures of obesity: (i) Body Mass Index (BMI) criteria and, (ii) Waist-Hip circumference ratio (WHR).[21] I also create metrics for cognitive functioning and motor balance. Cognitive functioning is based on Mini-Mental State Examination (MMSE) attributes in the LASI data. [22] Motor balance is based on two components: (i) grip strength and, (ii) balance test. For cognitive functioning, I create two binary variables: (i) Indicating poor cognitive functioning (MMSE score ≤ 15), where mean cognitive score in the sample is 15 and, (ii) A dummy variable equal to 1 if cognitive score ≤ 19, which is the cut-off for mild cognitive impairment. Grip strength is an indicator variable=1 if an individual's grip strength (maximum force exerted by the hand muscles, measured in kilograms (kg) is below the age-group and gender-specific cutoff. The balance variable is defined as 1 if an individual's score, based on a timed walk and tandem balance test, is below the cutoff value. For full details on the variable construction, refer to the Appendix

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.[23] 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) and agrochemical health risk index index (chronic respiratory disease, urogenital problems, cancer) Aggregating measures within a domain, such as metabolic syndrome, enhances statistical power. The summary index is calculated as the average of standardized z-scores for each component, where the z-score is obtained by subtracting the mean and dividing by the standard deviation. The higher the value of these indices, worse is the outcome. Table 1 provides summary statistics for the demographics and health outcomes in the LASI data.

[19]26% of the individuals either migrated to another district or another state.

[20]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.

[21]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. The medical literature suggests that WHR is a better indicator of visceral fat, which is more metabolically active and associated with greater health risks, whereas BMI doesn't differentiate between muscle and fat mass [Després, 2006, Kuk et al., 2006]. WHS is considered to be a more reliable measure for predicting obesity-related mortality and morbidity because it reflects abdominal fat distribution, which is a critical factor in health outcomes [Vazquez et al., 2007, Janssen et al., 2004].

[22]MMSE is a 30 point questionnaire that is used to measure cognitive impairment (For reference in economics, see Banerjee et al. [2018]). It's components are orientation, word recall, object naming, number series, computation, executive function, drawing.

[23]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.

3.4 Nutrition Outcomes

National Sample Survey: Consumption Expenditure (1999)

My analysis utilizes data from the 55th round (1999-2000) cross-sectional survey on consumption expenditure conducted by the National Sample Survey Organization (NSSO). As discussed in the introduction, consumption data from before the introduction of HYV seeds are unavailable, so this round is used to assess the impact on nutrition. The survey includes approximately 70,000 rural households (located in 8,000 villages) and 45,000 urban households (located in 4,500 urban blocks). Survey weights will be applied to ensure national representativeness. 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 per 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) and then dividing by household size. The surveys also provide data on non-food expenditures and household demographics and characteristics.

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 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

Potential Productivity Gains

I construct a measure of predicted productivity gains for wheat and rice by capturing the shift from traditional, low-input, rainfed farming—typical of pre-Green Revolution agriculture—to the potential gains from high-input, irrigated systems with the adoption of Green Revolution technologies. Wheat and rice are complementary crops grown in different seasons—wheat in the Rabi (winter) season and rice in the Kharif (summer/monsoon) season— allowing farmers to cultivate both within the same agricultural year. By using the predicted gains for both crops, I capture a district's overall potential gains. Districts with higher potential gains in either wheat, rice, or both are more likely to adopt HYVs.

The potential productivity gains is constructed 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 predicted productivities at high input level and irrigation for wheat and rice; and, P^l_w and P^l_r are predicted productivities at low input level and rainfed condition for wheat and rice in district d.

HYV Adoption and Potential Productivity Gains

First, I start by documenting the relationship between potential productivity gains and the share of hyv area under wheat and rice in total cultivated area. To do that, I run a simple difference-in-differences (DID) model to study adoption of high-yield varieties in districts with higher potential productivity gains:

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

where $ShareHYV_{d,t}$ is the share of HYV wheat and rice area in district d in year t, Post^{1965}_t 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, δ_d and τ_t are district and time fixed effects. Standard errors are clustered at the district level.

Crop Diversity

Next, using the same estimating equation, I examine how potential productivity gains influenced crop diversity by analyzing the changes in area allocation across different crops. This helps identify which crops expanded or declined with the increase in HYV adoption and highlights which crops were substituted as a result. I run the following equation:

$$Cropdiv_{d,t} = \theta(\text{ProdGain\_wr}_d \times \text{Post}^{1965}_t) + +\beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{d,t} \tag{2}$$

where $Cropdiv_{d,t}$ is the Shannon Diversity Index (DI)= $\sum_{i=1}^{n} p_{i,d,t}\ ln(\frac{1}{p_{i,d,t}})$, where $p_{i,d,t}$ is the area planted under crop i in district d, year t. I use this measure of crop diversity because it accounts for both the variety of crops and the evenness of their distribution. A higher value indicates greater diversity. In addition, I employ alternative specifications to ensure robustness, which I will discuss in the results section.

Flexible Event-Study Specification

I also estimate a fully flexible specification that takes the following form:

$$Y_{d,t} = \sum_{t=1957}^{2007} [\gamma_t (Year_t \times \text{ProdGain\_wr}_d)] + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{d,t} \tag{3}$$

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 specification aims to check for pre-trends and observe post-1965 trends across districts with different potential productivity gains.

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:

$$Y_{i,d,t} = \theta \ (\text{ProdGain\_wr}_d \times \text{Post}_t^{1965}) + \beta_1' X_{i,d,t}^1 + \beta_2' X_{d,t}^2 + \delta_d + \tau_t + \varepsilon_{i,d,t} \tag{4}$$

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 in-utero 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 level.

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:

$$Y_{i,d,t} = \sum_{n=1}^{6} \theta_l^{pre} \ (\text{ProdGain\_wr}_d \times \gamma_n) + \sum_{n=8}^{13} \theta_l^{post} \ (\text{ProdGain\_wr}_d \times \gamma_n) + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{i,d,t} \tag{5}$$

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.

5. Results

5.1 Adoption of high-yielding varieties of 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 adds a series of controls: Annual mean precipitation, temperature and baseline district characteristics: 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 interacted with year fixed effects. These controls allow for differential trends based on initial geographical and socio-economic characteristics. Despite the inclusion of these controls, designed to capture the role of initial geographic and economic characteristics on trends in share of HYV adoption, the relationship remains robust in terms of 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.

Even though high-yielding varieties were not introduced in India until 1966, I estimate euqation 3 to examine the relationship between potential productivity gains and share of HYV adoption of wheat and rice in each time period post 1965. Figure 4 shows the trend in the share of HYV adoption of wheat and rice in total cultivated area over time. Since there is no HYV before 1966, where the area planted is zero across all districts before this time. Consequently, no differential trends existed prior to the Green Revolution. I run a similar regression to examine the relationship between potential productivity gains and the share of area under wheat and rice from 1957-2007. Since direct data on HYV adoption prior to 1966 is unavailable, this serves as a proxy for pre-existing trends. Appendix Figures A.8 and A.9 show no significant pre-trends, suggesting no differential crop cultivation patterns before 1966.

It is important to highlight that potential productivity gains are derived from theoretical models of potential yield, which are calculated using agro-climatic characteristics. Hence, these values are not likely influenced by potentially endogenous characteristics or observed production patterns. Additionally, I provide evidence that the relationship between potential productivity gains and share of hyv adoption does not likely depend on district-level variations in initial characteristics.

5.2 Effect on crop diversity

Table 3 estimates the equation 2 to examine the relationship between potential productivity gains and crop diversity measured as shannon DI. Column (1) includes only potential productivity gains and fixed effects, showing a strong negative relationship between crop diversity and potential productivity gains. I include same set of controls as above in Column (2) to account for differential trends based on initial geographical and socio-economic characteristics. The negative relationship remains strong both in magnitude and statistical significance. For simplicity, if we assume that the area grown under each crop is equally distributed, the mean value of 1.5 of shannon DI corresponds to 4.5 crops. Now, a one standard deviation increase in potential productivity gains (1.26 tonnes per hectare) leads to a decline in crop diversity from 4.5 crops to 3.8 crops. [24]

To further validate the empirical strategy,, I estimate the flexible specification in equation 3. This approach allows me to investigate whether districts with higher potential productivity gains exhibited differential trends in crop diversity before the introduction of HYVs. The absence of pre-existing trends would validate the key assumption that districts with varying levels of exposure to productivity gains would have followed similar trajectories in crop diversity had the Green Revolution not occurred. And if adoption of Green Revolution technologies affected district outcomes, we should see district with higher gains in potential productivity of wheat and rice diverge from other districts starting from 1966.

In the Figure 5, prior to the introduction of HYVs, as indicated by the period leading up to the vertical line, the estimated coefficients remain close to zero and are statistically insignificant. This suggests that potential productivity gains from the shift from traditional varieties- to Green Revolution technologies for wheat and rice were not associated with any pre-existing trends in crop diversity before the onset of the Green Revolution. It also highlights that districts more suited for HYV adoption were on a similar trajectory in terms of crop diversity as those less suited before the Green Revolution. After the release of HYVs, however, we observe a marked decline in crop diversity, which intensifies over time.

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

Following the analysis of the overall decline in crop diversity, I next focus on identifying which specific crops have experienced a reduction in cultivated area. Different crops are grown in specific seasons, and potential productivity gains from adopting HYV wheat and rice may drive crop substitution. For instance, during the Rabi (winter) season, crops like wheat, barley, and chickpea are cultivated. As potential 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, and higher potential gains from rice might lead to increased land allocation for rice at the expense of other Kharif crops. To analyze this, I estimate a similar equation as 1, but now the dependent variable is area under a particular consumption crop.[25] This analysis highlights the shifts in crop cultivation, revealing which crops were most impacted by the likely adoption of high-yielding wheat and rice varieties. Figure 6 shows the effect on area under different consumption crops. The results suggest that the area under wheat and rice increases with potential productivity gains (area

[24] 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

[25] 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.

under sorghum and soybean increased as well), but area under barley, pearl millet, chickpea, minor pulses and groundnut declined.

Declining Crop Diversity and Shifts in Production

Having established that the area under certain crops has declined while wheat and rice have expanded, it is crucial to now examine the overall production of these consumption crops. Understanding production trends is important because it sheds light on how the shift in cultivated area translates into actual output, which has direct implications for diverse food availability, which is essential for nutritional security add citation. Figure 7 shows the effect on production of different consumption crops. The results suggest that there is a statistically significant decline in production (measures in tonnes) of pearl millet, chickpea, minor pulses, pigeonpea, groundnut. The production of barley and finger millet, although declined, does not show statistically significant effects. Conversely, the production of maize and sorghum increased, but the estimates are either statistically insignificant or marginally significant. This reduction in the production of a variety of crops could limit the availability of diverse food options, potentially affecting diet and nutritional balance.

Although production of certain consumption crops has declined, it is possible that imports have been sufficient to maintain overall availability. While district-level data on the import and export of these consumption crops is unavailable, ICRISAT provides national-level data on per capita availability (kg/year), defined as production plus net imports per capita for the time period 1951-2006. This data is categorized into four main groups: 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 affected the overall availability. The Appendix Figure A.10 shows that while the per capita availability of wheat and rice has increased, it has decreased for lentils and coarse cereals. This trend also provides credence to the argument that the availability of diverse food options is being limited.

Availability of nutrients

Lentils, barley, pearl millet, and groundnut offer distinct nutritional benefits compared to wheat and rice, particularly concerning protein content and essential micronutrients and glycemic index add more with citations which are crucial for early-age development and preventing long-run cardio-vascular issues.

5.3 Effect on Health Outcomes

The fetal origin hypothesis [Barker, 1990] posits that environmental factors, particularly nutrition, during fetal and early childhood stages have long-lasting effects on health and disease risk later in life. Malnutrition during critical periods of development can lead to permanent changes in the body's structure, physiology, and metabolism, increasing susceptibility to not only chronic conditions such as cardiovascular disease, diabetes, and obesity; but also, impaired cognitive and motor development, emotional distress, and behavioral problems. The underlying mechanisms involve epigenetic changes, altered organ development, and disrupted hormonal regulation, all of which can predispose individuals to these conditions later in life. 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].

Adult Height

First, I assess the effect of potential productivity gains on height measured in centimeters. The fetal origins hypothesis extends to micronutrient deficiencies, including iron and folate deficiency, emphasizing the long-term impacts of inadequate prenatal nutrition on child health. Essential macronutrients like protein and micronutrients like iron, folate, zinc, and vitamins are crucial for physiological processes such as oxygen transport, DNA synthesis, and immune function. Nutrient deficiencies in the first 1,000 days of life can lead to stunting, which is not easily reversible and has long-term health and economic consequences add citations.

Table 6 estimates equation 4 to analyze the relationship between potential productivity gains and height. 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 (1.2 tonnes per hectares) leads to a 0.2 cm decline in height. This is in line with the literature that suggests that early life nutrition is crucial for height growth. Table A.1 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.

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.

I also examine the heterogeneity in the effects of potential productivity gains by gender. Table A.2 shows that while the negative relationship is statistically significant for both males and females, the estimates are higher for males. A 1 standard deviation increase in potential productivity gains results in a 0.25 cm decrease in height for males and a 0.2 cm decrease for females.

Metabolic Syndrome

Next, I examine the effect of potential productivity gains on metabolic syndrome index (MSI). The ”metabolic syndrome index” 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 presents the results of the effect of potential productivity gains on metabolic syndrome index and it's components. The effect of potential productivity gains on the metabolic syndrome index, as shown in column 1, is 0.012 and is statistically significant at the 5 percent level. The magnitude of the coefficient implies, a 1 standard deviation increase in potential productivity gains (1.2 tonnes per hectare) leads to a 0.014 standard deviation increase in the metabolic syndrome index. The coefficients are positive for all the components except chronic heart conditions, but only the coefficients for hypertension and diabetes are statistically significant. A 1 standard deviation increase in potential productivity gains leads to a 2 percentage point increase in hypertension and 0.8 percentage point increase in diabetes. Looking at the heterogenous effect by gender, the results in Table A.3 show that the effect of potential productivity gains on the metabolic syndrome index is driven by males.

Cognition

Given that micronutrient deficiencies can affect cognitive ad neurological development, I also examine the effects of potential productivity gains on cognitive functioning using the LASI data. Column 1 of table 8 shows the effect on cognitive imbalance index. The cognitive imbalance index 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.

Motor Skills

Micronutrient deficiencies in-utero can also affect motor skills. Column 1 of table 9 shows the effect on motor deficit index. The motor deficit index 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%.

PLacebo Health Outcomes

To validate the robustness of my findings, I also examine health outcomes unrelated to in-utero differential exposure, serving as a placebo check to ensure that the observed effects are not spurious. I estimate the effect of potential productivity gains on the probability of having a physical injury or disaster related health risk. The results in Table A.5 show that the there is no effect of potential productivity gains on physical injury or disaster related health risk.

5.4 Threats to Identification and Robustness Checks

Parallel Trends

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 the equation 5 for the health outcomes to examine the time-varying effects of potential productivity gains and rule out the presence of pre-trends.

Appendix figures A.13, A.14 and A.17 show the event-study estimates for the effect on height, metabolic syndrome index and cognitive imbalance index. For height, the estimates are close to zero for all the cohort before 1966, suggesting no differential trends in height before the onset of the Green Revolution. However, after 1966 the estimates are negative indicating a decline in height for cohorts born in districts with higher potential productivity gains. For metabolic syndrome index, there is a slight pre-trend for the cohort 1948-1950, but the coefficient, interestingly is negative. For cognitive imbalance index, the estimates are close to zero for all the cohorts before 1966, suggesting no differential trends in cognitive imbalance before the onset of the Green Revolution. However, after 1966 the estimates are positive, although insignificant indicating a slight increase in cognitive imbalance for cohorts born in districts with higher potential productivity gains.

I also look at the event-study estimates for the effect on diabetes, hypertension and neurological disorder in the Appendix figures A.15, A.16 and A.18. Apart from hypertension, there are no differential pre-trends for cohorts born between 1945-1965. For hypertension, I observe a few notable differences among cohorts born before the Green Revolution, with most coefficients, particularly the significant ones, being negative. This suggests that individuals born in districts with higher potential productivity gains before the Green Revolution are less likely to be diagnosed with these diseases. If anything, the pre-trends appear to be moving in the opposite direction.

Trends in Diet, Lifestyle, and Health Care Access

A potential threat to my identification strategy arises if recent trends in dietary habits (increased consumption of processed foods), lifestyle changes (more sedentary jobs and reduced physical activity), and differential access to health care are correlated with the gains in potential productivity from wheat and rice following the Green Revolution. If these trends disproportionately align with districts that are more likely to experience higher potential productivity gains, they could confound the estimated effects.

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

Appendix Tables A.10- A.13 show the results of the effect of potential productivity gains on height, 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 magnitude of the effect on height is stable and significant at 10% level. The estimates are positive for metabolic syndrome index but statistically insignificant. Within the components, the estimates for hypertension is positive and significant at 5% level. The estimates are positive for cognitive imbalance index and motor deficit index, but statistically insignificant.

Appendix Tables A.14- A.17 show the results of the effect of potential productivity gains on height, metabolic syndrome index, cognitive imbalance index and motor deficit index, controlling for the trends in the share of health care centres as well. Since, the baseline data on share of health care centres is only available for 140 districts, there is a fall in number of observations. However, the results are consistent with the previous findings. The magnitude of the effect on height is negative and significant at 1% level. The estimates are positive for hypertension and significant at 5% level. I also find 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 5% level and driven by the grip strength deficit.

Other in-utero exposure

Although, in my approach I control for fertilizer exposure at year of birth, Green Revolution might have influenced height and other health outcomes through higher pesticide exposure which is unrelated to nutrition. For instance, shifts towrds HYV wheat and rice becuase of higher potential productivity gains can lead to increased exposure to chemical pesticides which could negatively impact health. [Eskenazi et al., 2004, Jaacks et al., 2024, Calzada et al., 2023] affect of pesticide on fetal development and low birth weight which could affect height. Similarly pesticide exposure has been linked to metabolic syndrome and cognitive imbalance

Pesticide exposure is likely higher for individuals born in rural areas. However, dietary changes may also be pronounced in rural areas, which can make the heterogenous result difficult to interpret.

Robustness

To further validate my findings, I conduct an additional robustness check by including district-specific trends. This accounts for any time-varying factors within districts that were not envisioned above, ensuring that the results are not driven by underlying district-level trends unrelated to the introduction of HYV technology Appendix Tables A.6- A.9 show the results after controlling for district trends. The negative effect on height remains consistent in magnitude but loses statistical significance after controlling for district trends. This change in significance likely reflects a reduction in statistical power due to the inclusion of these trends. However, the coefficient sign for the metabolic syndrome index changes after including district trends, indicating sensitivity to these trends. This flip in sign may result from district trends are absorbing much of the variation in the independent variable. The results for cognitive imbalance and motor deficit are positive but statistically insignificant.

5.5 Alternative Specifications

Until now, the analysis has utilized cross-sectional variation in potential productivity gains, interacted with a post variable, to assess the effect on outcomes. As an alternative specification, I incorporate exogenous time variation from the adoption of high-yielding varieties (HYV) of wheat and rice in South Asian countries (Pakistan, Bangladesh and Nepal), which is independent of district-level decisions in India. This approach leverages variations in HYV adoption rates across the region as an external source of variation. Specifically, I construct the instrument by interacting the adoption rates of wheat and rice in other South Asian countries with the potential productivity gains for these crops, respectively. This interaction provides continuous variation and helps isolate the impact of productivity gains from local biases, offering a robust alternative to the cross-sectional variations used previously.

I use the following independent variable 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 4 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 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.

Appendix Tables A.22- A.25 show the results of the effect of new exposure variable on height, metabolic syndrome index, cognitive imbalance index and motor deficit index. The results are consistent, and slightly larger in magnitudes compared to the previous findings. The negative effect on height and positive effect on metabolic syndrome index is statistically significant at 1% level. Moreover, I find statistically significant positive effect on cognitive imbalance stemming from higher likelihood of neurological disorder. I find that one standard deviation (2.04 tonnes per hectares) increase in potential productivity gains increases the likelihood of reporting neurological disorder by 1 percentage point. The point estimates for motor deficit index are positive, and significant at 1 percent level. A one standard deviation increase in potential productivity gains leads to an increase in motor deficit by 0.08 standard deviations.

6. HYV Adoption and Nutrition

The introduction of high-yielding varieties of staples like rice, wheat, and maize increased overall food production but led to a decline in the cultivation of diverse crops. This reduction in biodiversity negatively impacts nutrition, as diets become less varied and rely heavily on staple grains, which lack essential micronutrients. Optimists highlight that the Green Revolution improved household calorie intake and national food security [Pinstrup et al., 1991]. On the other hand, pessimists argue that the focus on monocropping reduced diversity, leading to lower consumption of micronutrient-rich foods like lentils and coarse grains [Bouis, 2000].There is surprisingly little empirical evidence on how these agricultural advances directly affect nutrition outcomes [Pinstrup-Andersen, 2013, Ruel and Alderman, 2013]. Headey and Hoddinott [2016] highlight this issue in Bangladesh in a correlational study, where rice yield growth improved food security and income but did not lead to better dietary diversity or significant nutritional benefits for children.

In many parts of India, poor market integration worsens these nutritional challenges. High spatial price dispersion means that agricultural commodity prices vary widely across markets, hindering the distribution and availability of diverse foods. Despite investments in infrastructure to reduce trade costs, such as rural roads and communication networks, price dispersion remains high [Kapur and Chatterjee, 2016]. This suggests that many regions consume what they produce locally, limiting access to a varied diet. Consequently, even if income increases from higher productivity in staple crops, the lack of market integration prevents a more nutritious and diverse diet, perpetuating nutritional deficiencies.

As discussed earlier, there is a lack of district-level household or individual consumption data before 1987. Hence, I present the results of the relationship between crop diversity and nutrient intake using the 1987 and 1999 NSS household consumption data. Two caveats of this study are: (i) the analysis relies on cross-sectional data, which may not capture the time-varying effects of HYV adoption on nutrition, and (ii) the data does not permit examination of sex-based heterogeneity in the effects, as it is not available at the individual level.

I run the following estimating equation:

$$Y_{i,s,d} = \beta \text{Share\_HYV}_{d,s} + \gamma \mathbf{X}^1_{i,d,s} + \eta \mathbf{M}_{d,s} + \tau_s + \varepsilon_{i,s,d} \tag{6}$$

where $Y_{i,s,d}$ is the outcome variable for household i residing in district d and state s. The outcome variables are: (i) Share of wheat and rice in total cereal and lentils consumption, (ii) calorie intake, carbohydrate intake, iron intake, zinc intake, vitamins intake, protein intake and calcium intake. All outcome variables are measured in per capita per 30 days. $\mathbf{X}_{i,d,s}$ is a vector of household-level controls: caste, religion, household size, share of educated female, rural dummy, main occupation, $\mathbf{M}_{d,s}$ is a vector of district-level controls: population density in 1981, market integration in 1981, yield of wheat and rice in 1961. τ_s is state fixed effects.

Table 12 presents the results of the OLS estimation of the relationship between HYV adoption and nutrient intake using NSS- Consumption Expenditure data from 1999-2000.

The OLS estimates are statistically significant in almost all the columns. Share of HYV adoption is indeed positively associated with higher share of wheat and rice consumption, higher calorie and carbohydrate intake and lower nutrient intake.

The corresponding estimates for crop diversity are shown in the Appendix.

7. Agrochemical Use and Health Outcomes

The Green Revolution was not just about the adoption of high-yielding varieties of wheat and rice. It also involved the use of agrochemicals like fertilizers and pesticides to boost crop yields.citations explain the mechanism of transfer an studies why more porminent for rural areas

Table 10 presents the results of the effect of potential productivity gains on agrochemical related health risks. A one standard deviation increase in the exposure to potential productivity gains in-utero leads to a 0.6 percentage point increase in the likelihood of reporting respiratory dissorder. Table 11 presents the heterogeneity results comparing the effect of potential productivity gains on agrochemical related health risks for individuals born in rural and urban areas. The estimates are strongly significant and higher in magnitude for those born in rural areas. This in line with the argument that rural areas are more likely to be exposed to agrochemicals due to the close porximity to agricultural fields.

8. Conclusion

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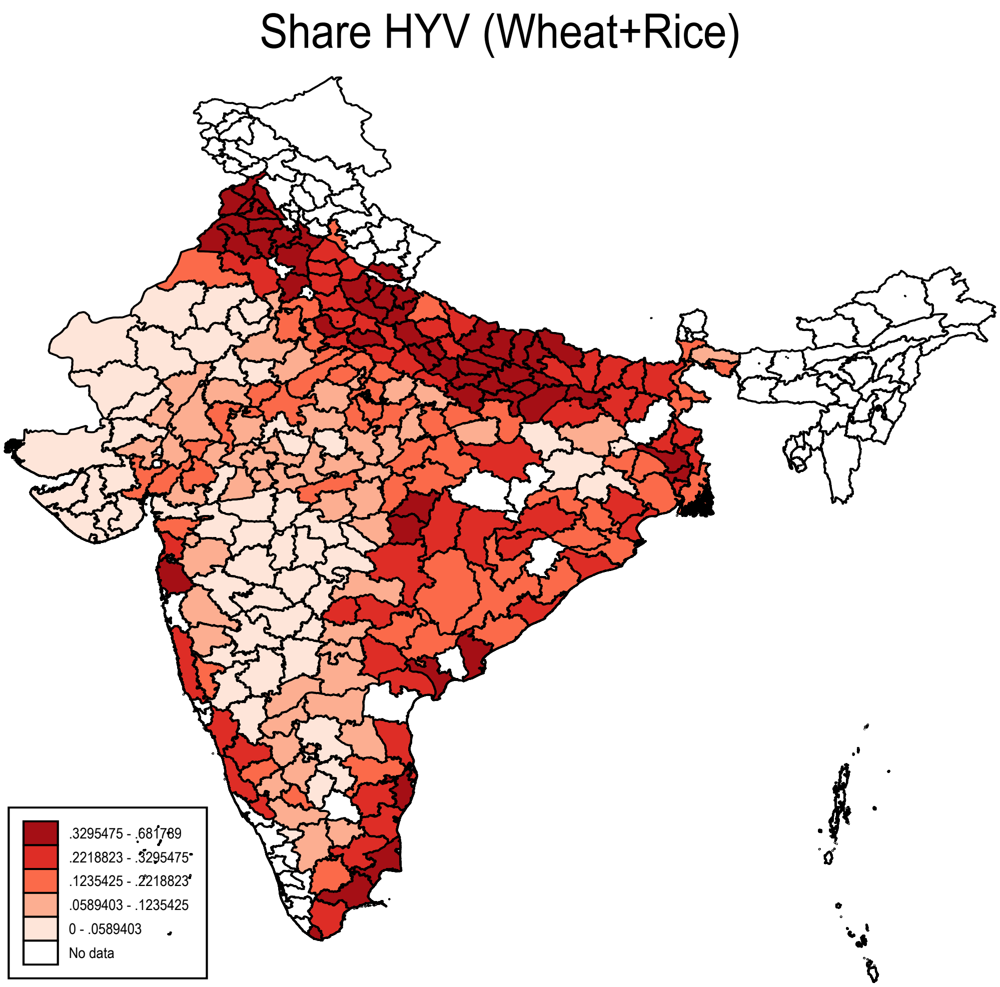
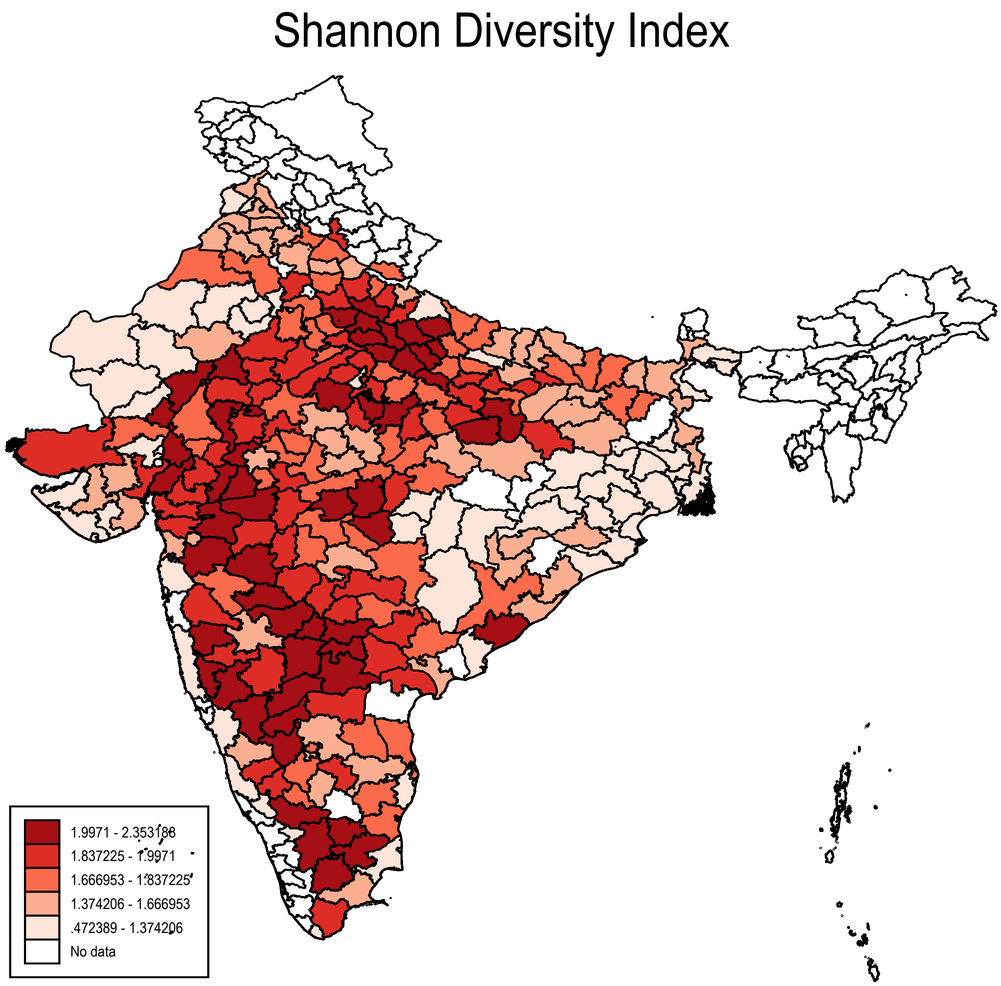
Tables and Figures

Figures



Source: Indian Agriculture and Climate Dataset

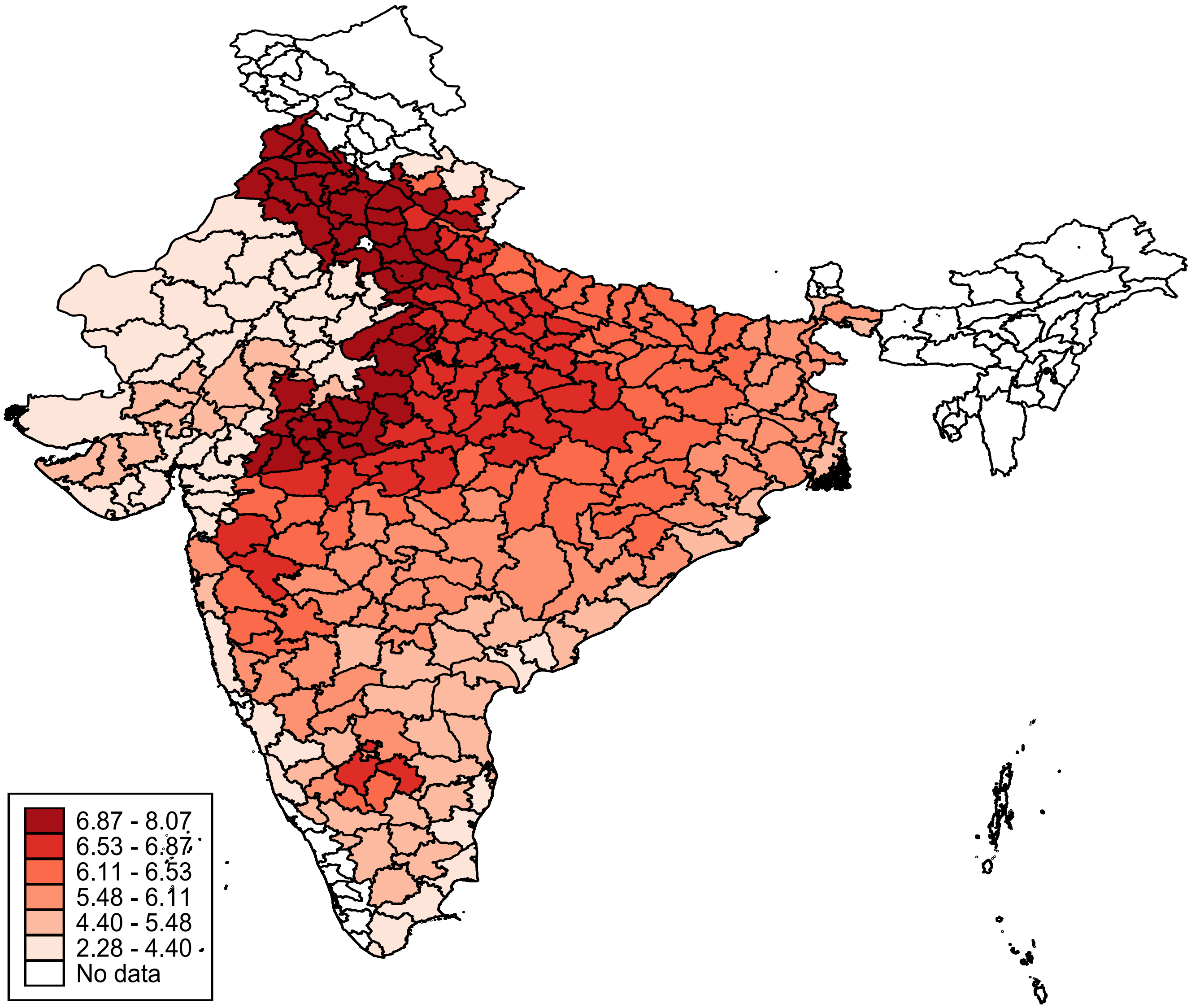
Figure 1: Average Share HYV adoption of wheat and rice in total cultivated area (1966-2007)



Source: Indian Agriculture and Climate Dataset

Figure 2: Average crop diversity measured between (1957-2007)

Figure 3: 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.

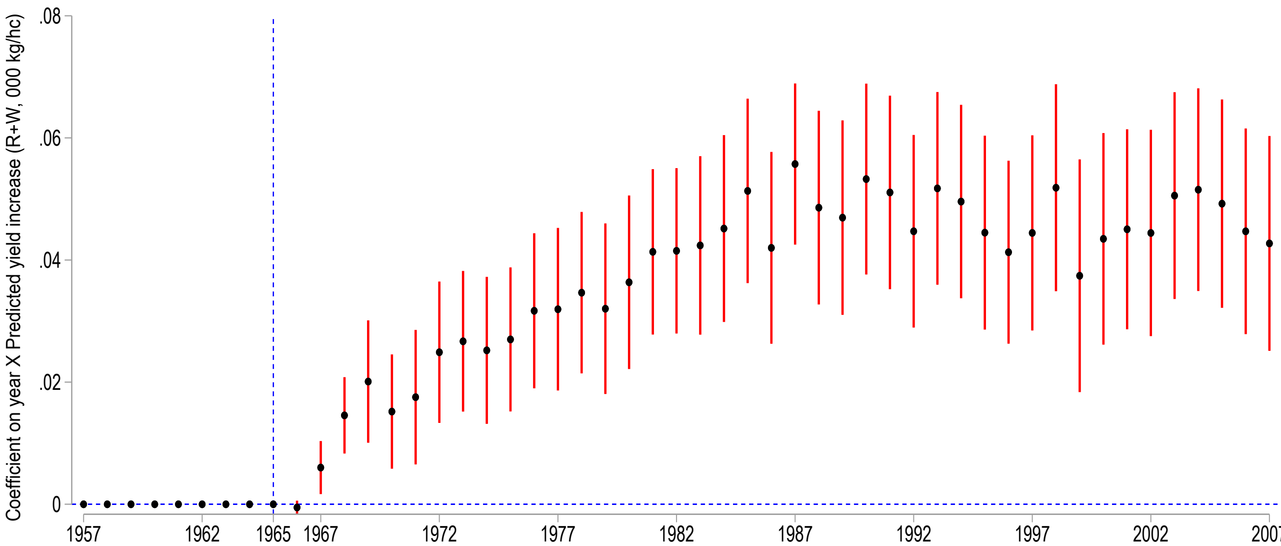
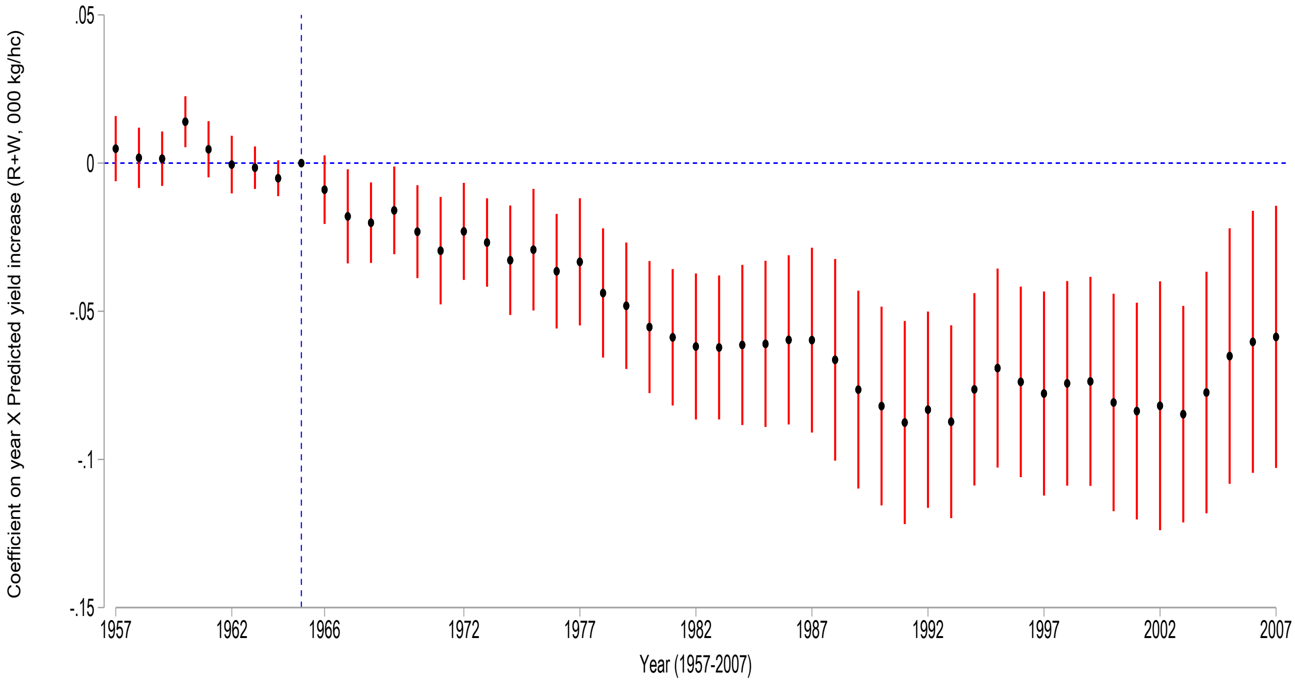


Figure 4: Event study estimates: Share of HYV adoption of wheat and rice in total cultivated area

Notes: This figure plots the coefficients from estimating equation 3 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 5: Event-study estimates for the effect on crop diversity



Notes: This figure plots the coefficients from estimating equation 3 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 6: Effect on area (in hectares) under different consumption crops

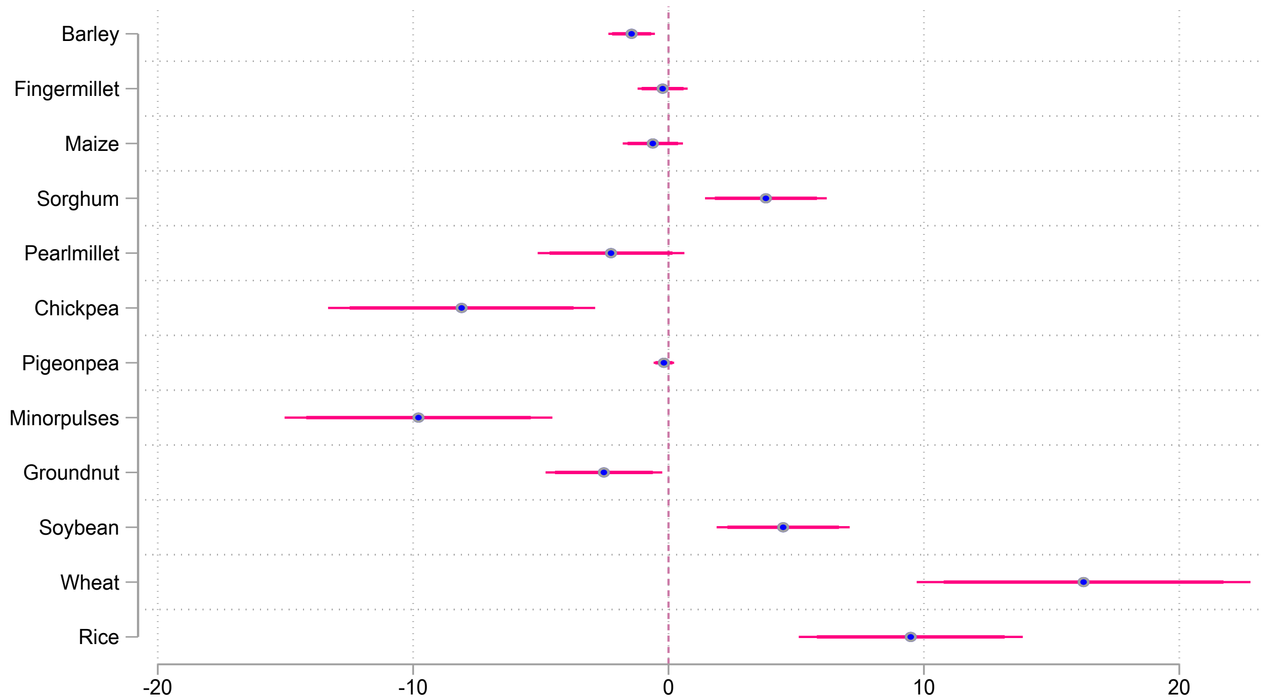


Figure 7: Effect on production (in tonnes) of consumption crops

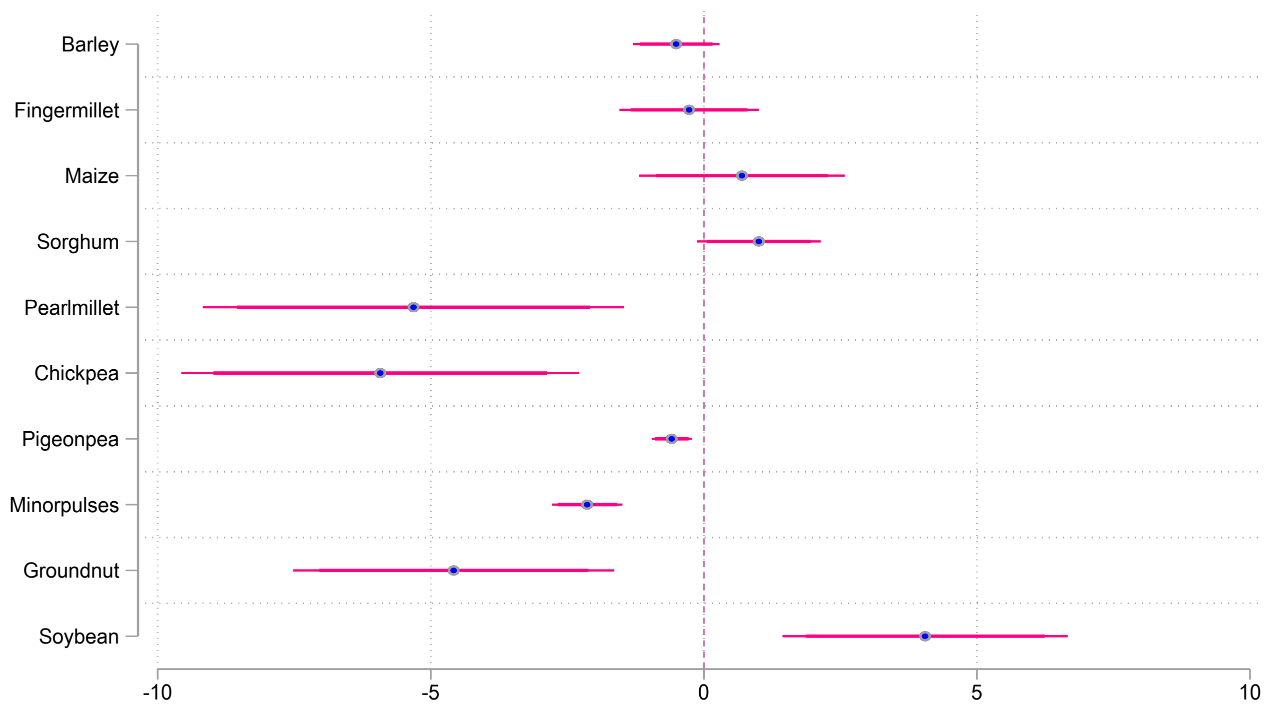
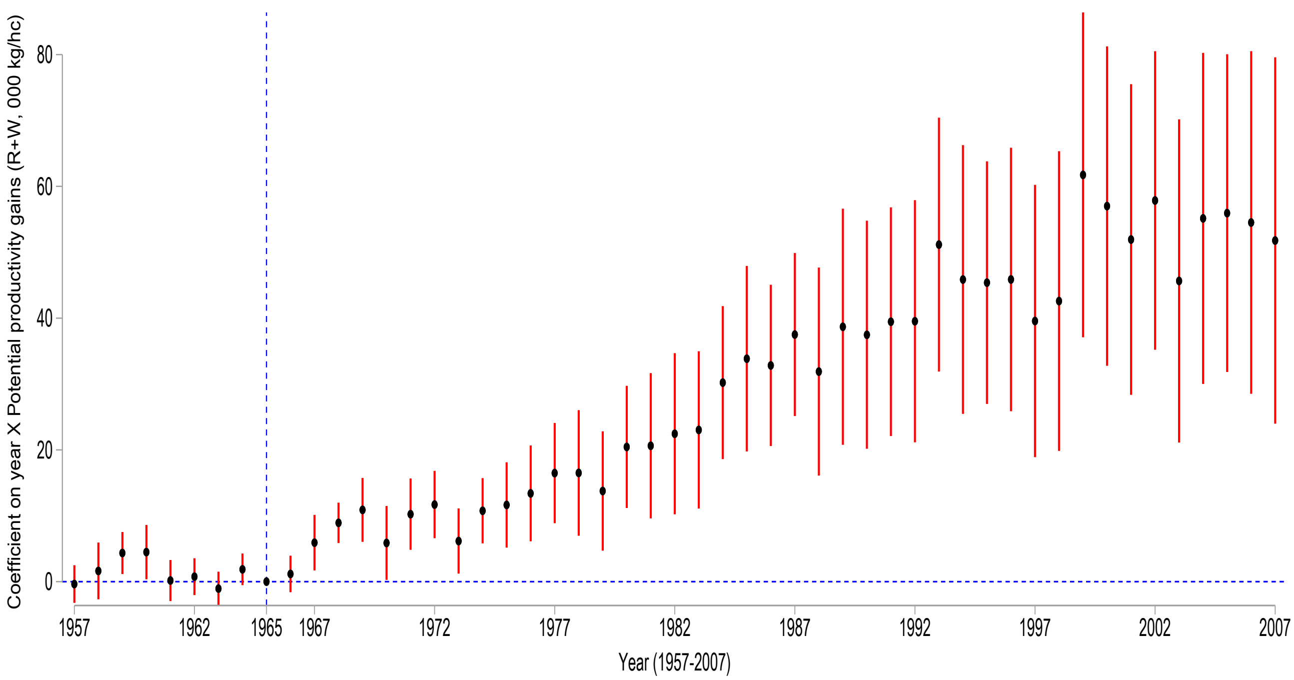
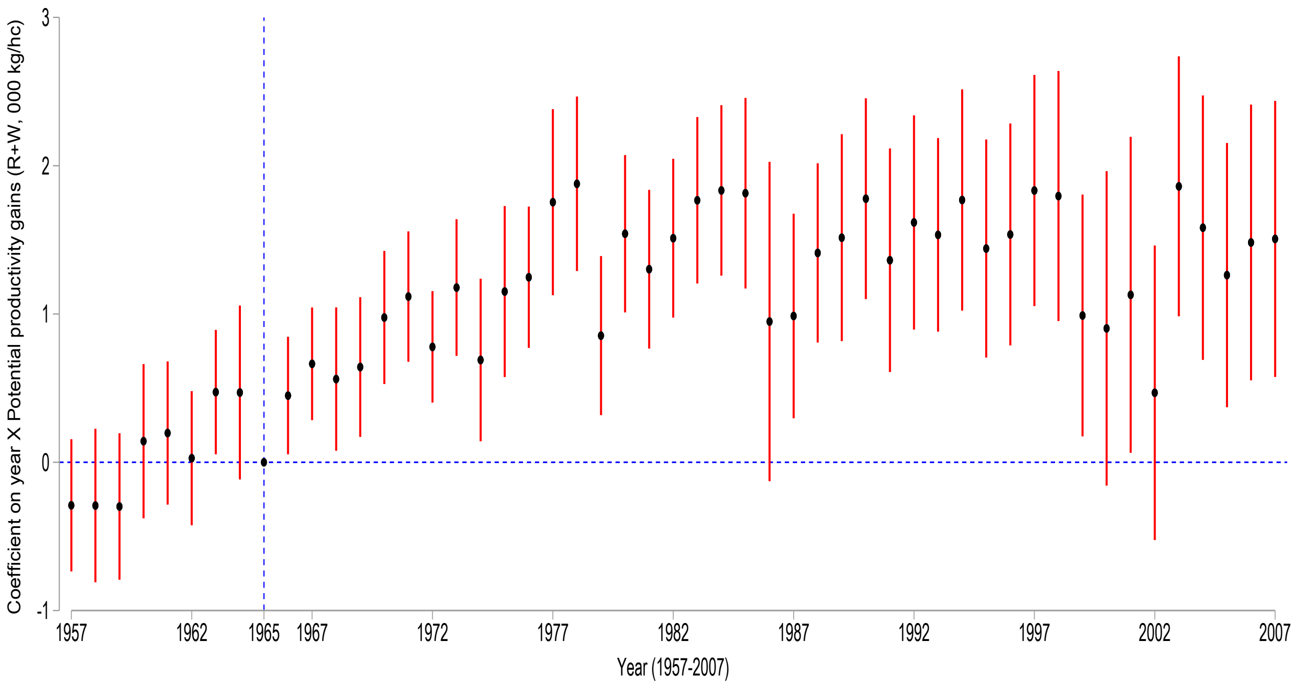


Figure 8: Event study estimates of total calorie production



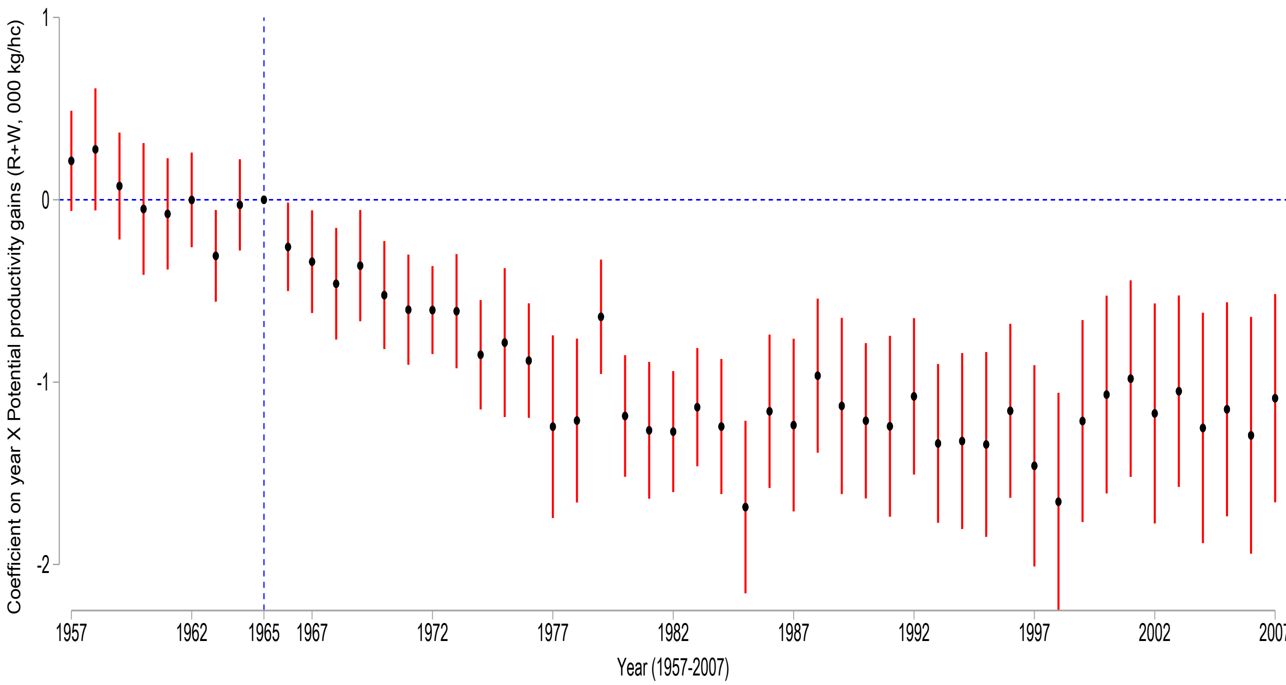
Notes: This figure plots the coefficients from estimating equation 3 using total calorie produced (000 kcal) as the dependant variable. The caloric calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory 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 9: Event study estimates of carbohydrates per calorie produced



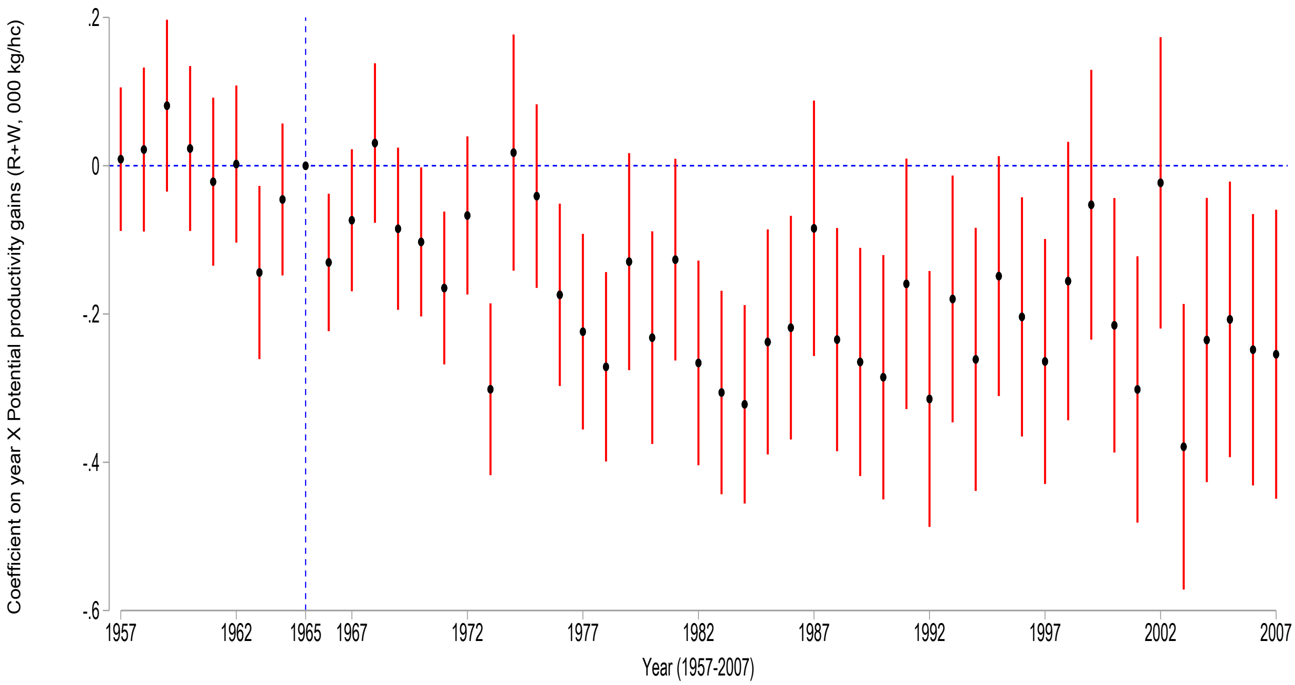
Notes: This figure plots the coefficients from estimating equation 3 using carbohydrate produced per calorie produced (g/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. 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 10: Event study estimates of protein per calorie produced



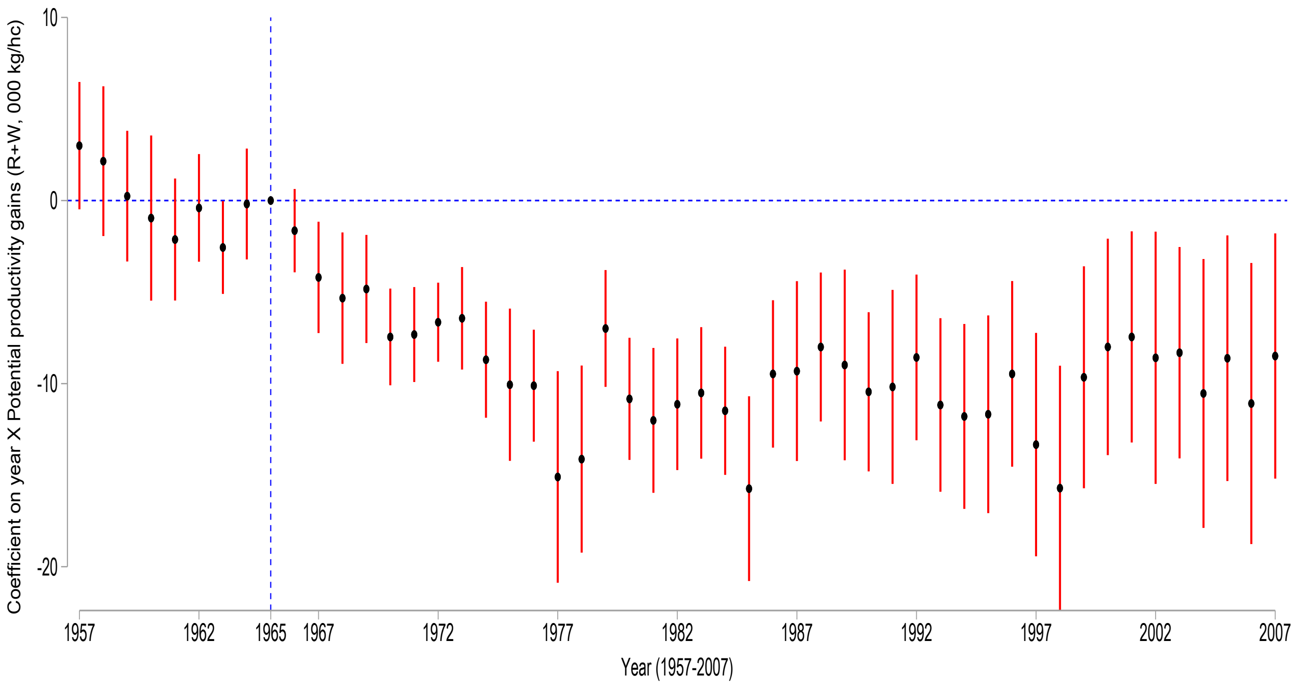
Notes: This figure plots the coefficients from estimating equation 3 using protein produced per calorie produced (g/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. 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 11: Event study estimates of iron per calorie produced



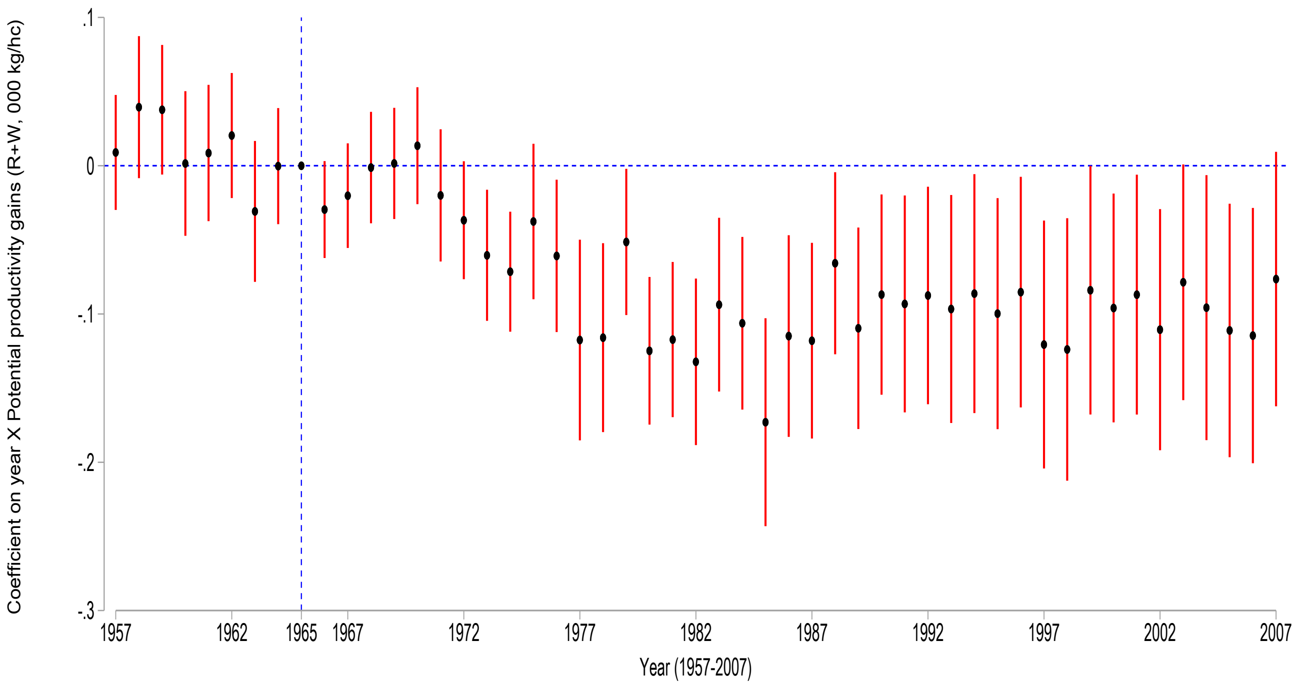
Notes: This figure plots the coefficients from estimating equation 3 using iron produced per calorie produced (mg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The 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 12: Event study estimates of folate per calorie produced



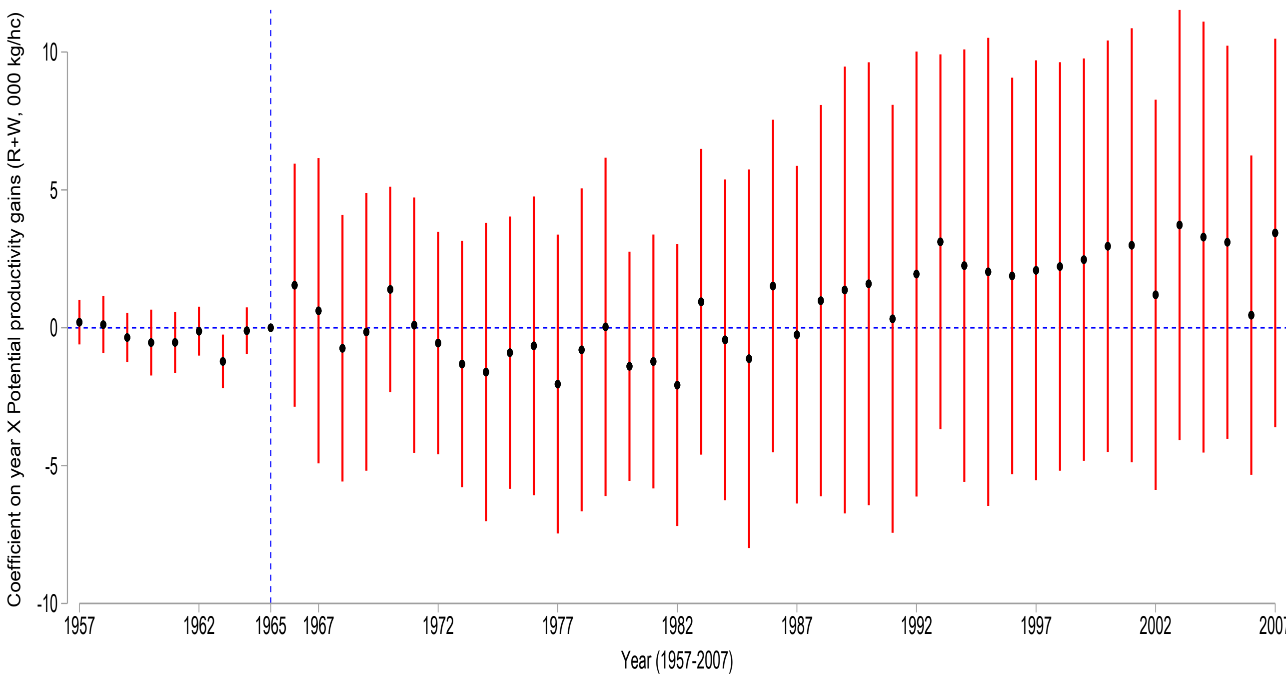
Notes: This figure plots the coefficients from estimating equation 3 using folate produced per calorie produced (μg/000 kcal) as the dependant variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. 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 13: Event study estimates of zinc per calorie produced



Notes: This figure plots the coefficients from estimating equation 3 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 14: Event study estimates of calcium per calorie produced



Notes: This figure plots the coefficients from estimating equation 3 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 (W,R)^{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 (W,R)^{1957} x $\mathbf{I}_t$	No	Yes

Notes: Each column presents the results from estimating equation 2. 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) Calories	(2) Carb.	(3) Protein	(4) Iron	(5) Folate	(6) Zinc	(7) Calcium	(8) Vit B1	(9) 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

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 2. 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)	(3)	(4)	(5)	(6)	(7)
		BMI	WH-Ratio	Hypertension	Diabetes	Chronic Heart	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 4). 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 4). 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 4). 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 4). 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.

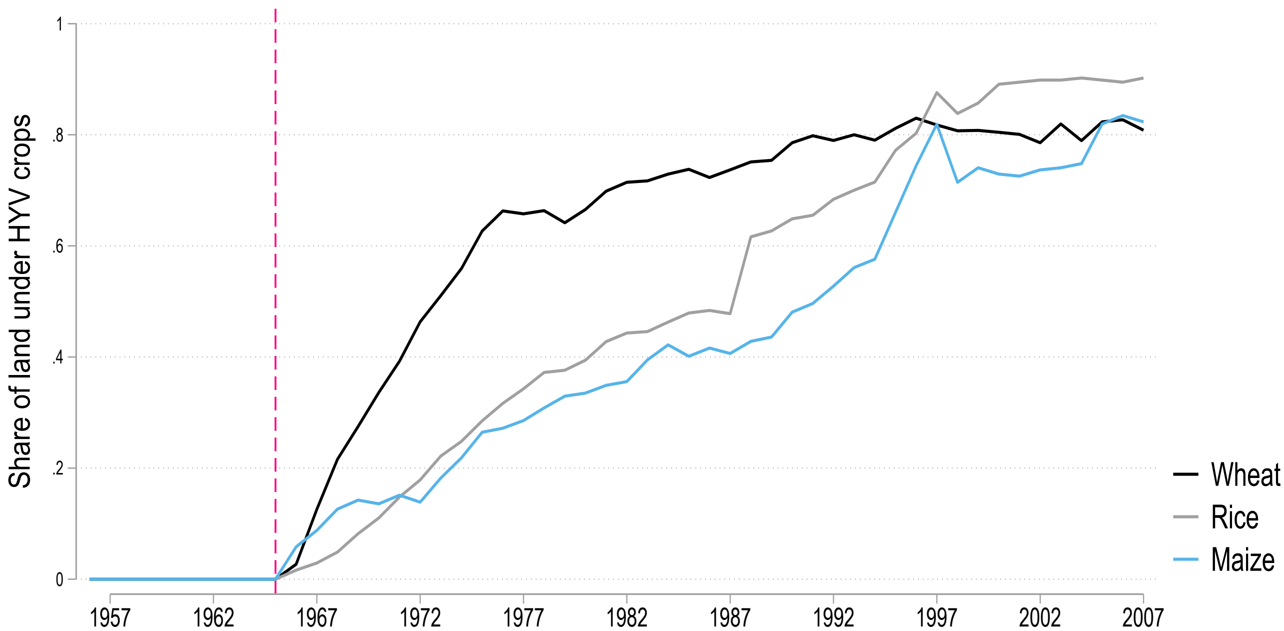
Table 12: HYV Adoption and Nutrient Intake

	1999 NSS: CE									
	Share(W+R)	Cal.(kcal)	Carb.(g)	Iron(mg)	Folate(μg)	Zinc(mg)	VitB1(mg)	VitB2(mg)	Calcium(mg)	Protein(g)
Share HYV	0.2***	5017.4***	1534.0***	-173.0***	-1103.8***	-56.9***	-15.5***	-4.9***	-1177.2***	-34.9
	(0.0)	(1237.6)	(311.0)	(27.7)	(210.3)	(13.3)	(2.9)	(0.8)	(302.0)	(37.6)
Observations	68219	69284	69284	69284	69284	69284	69284	69284	69284	69284
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	0.86	38421.71	8483.95	294.03	3097.34	244.02	26.83	12.00	2675.98	1208.37

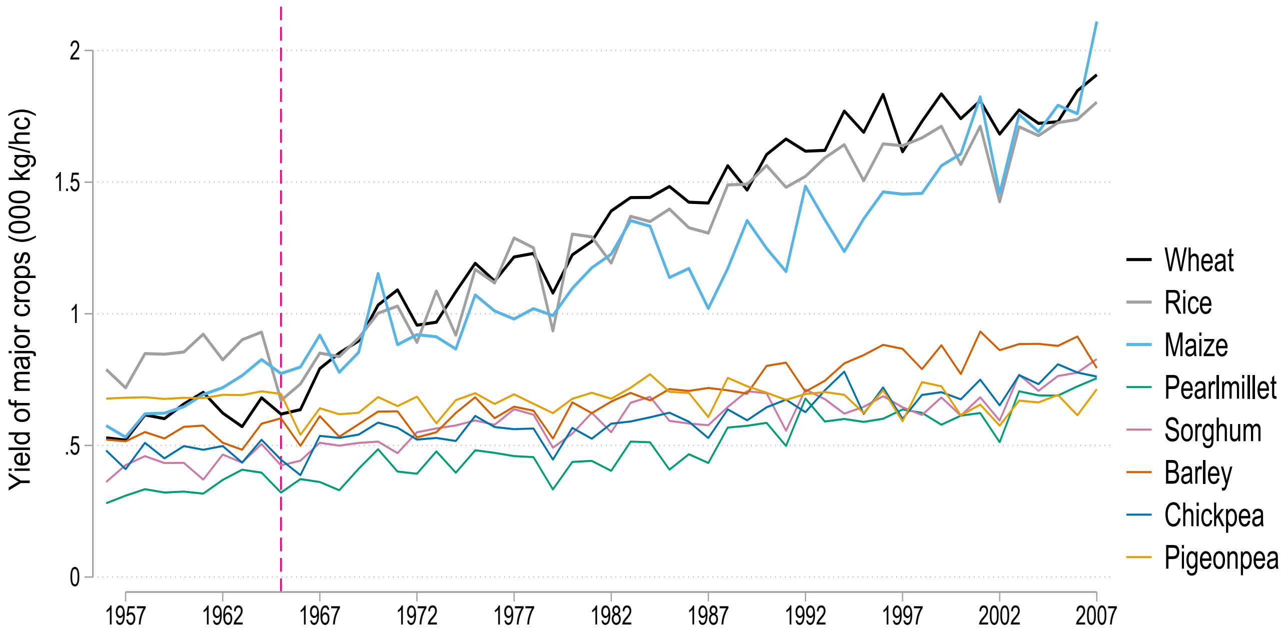
Notes: This table presents the relationship between crop diversity and nutrient intake. The regression include household socio-economic controls. State fixed effects are included. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

A. Appendix

2. Figures

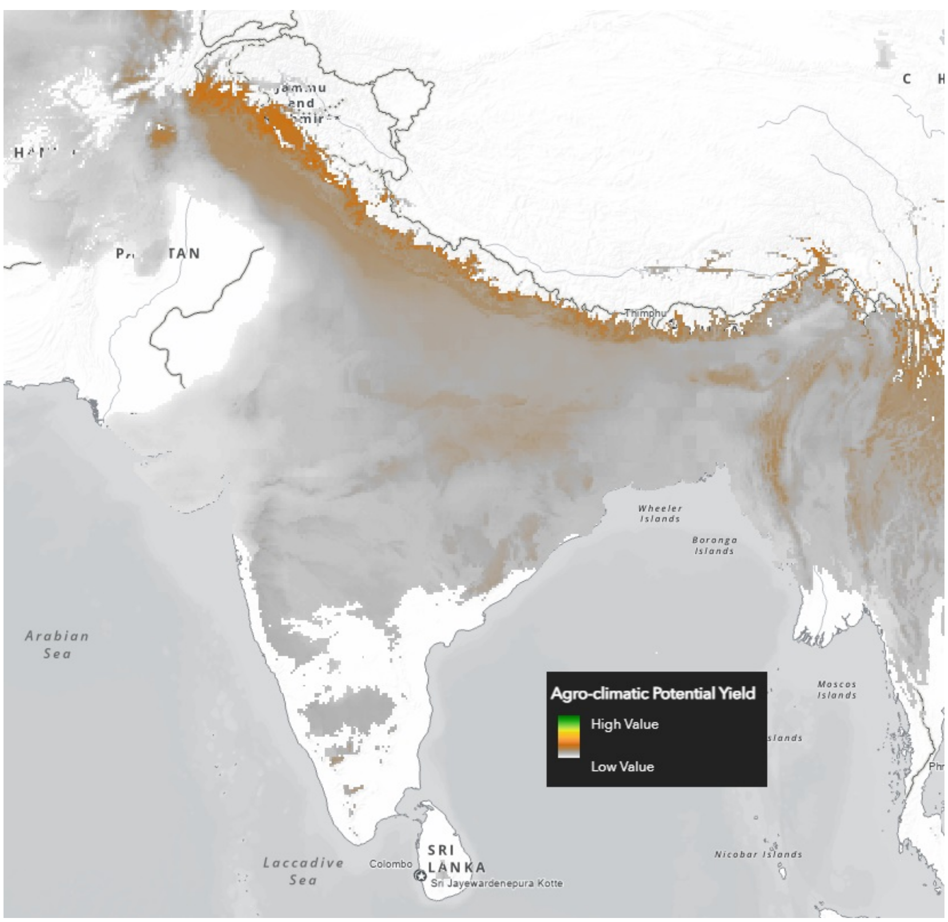


Source: Indian Agriculture and Climate Dataset, ICRISAT



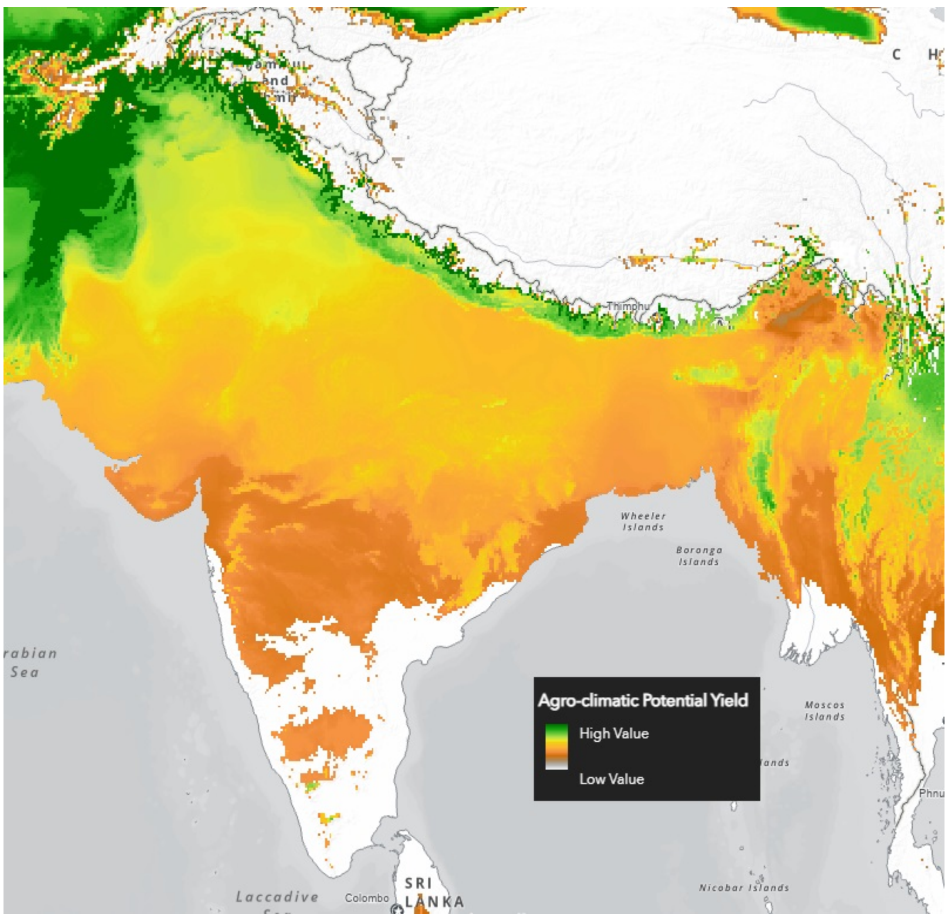
Source: Indian Agriculture and Climate Dataset, ICRISAT

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



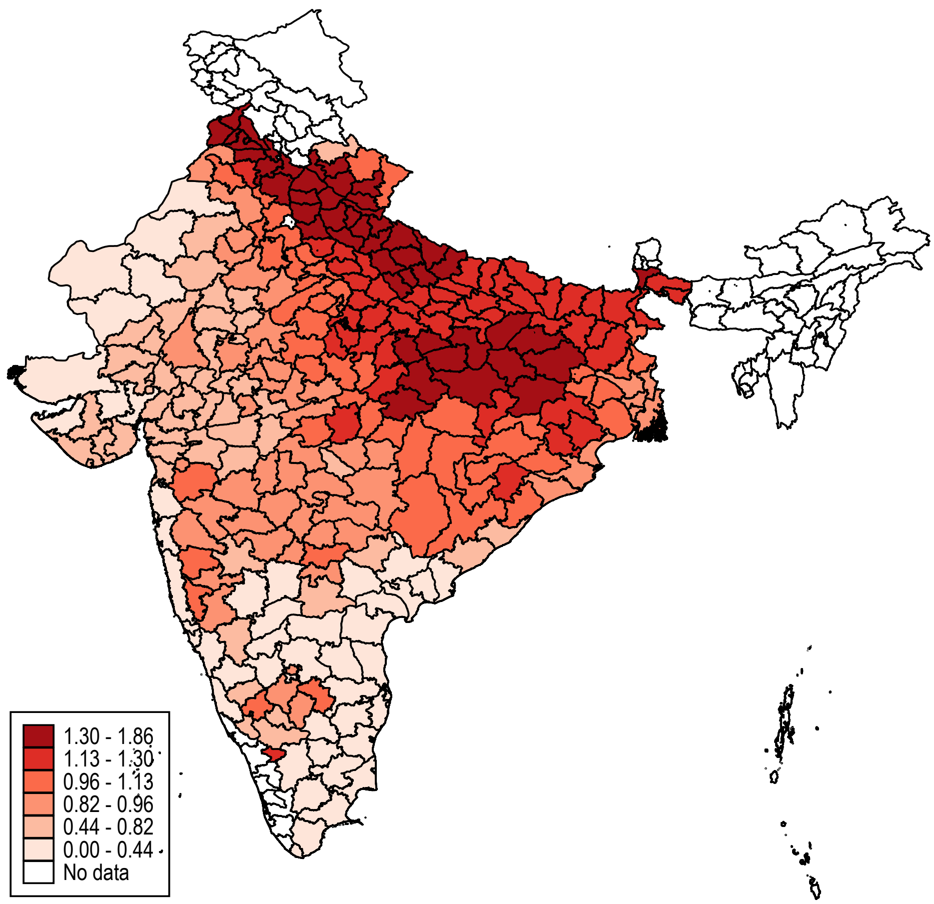
Source: FAO: GAEZ-v4

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



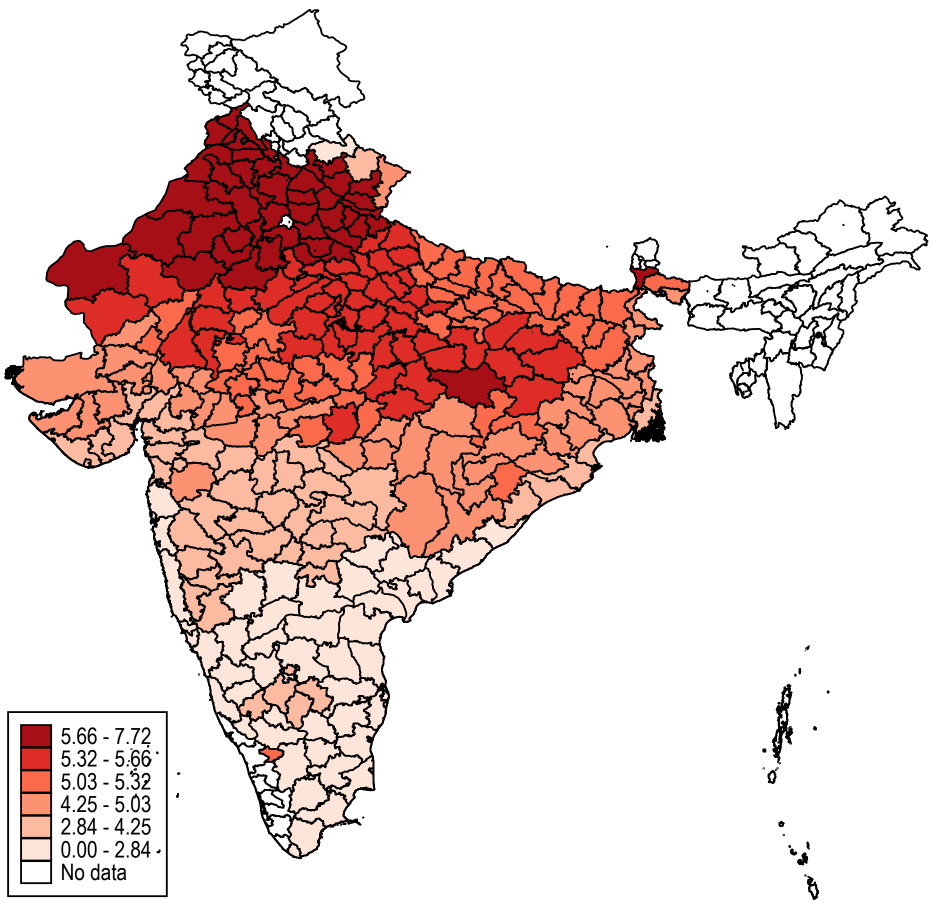
Source: FAO: GAEZ-v4

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



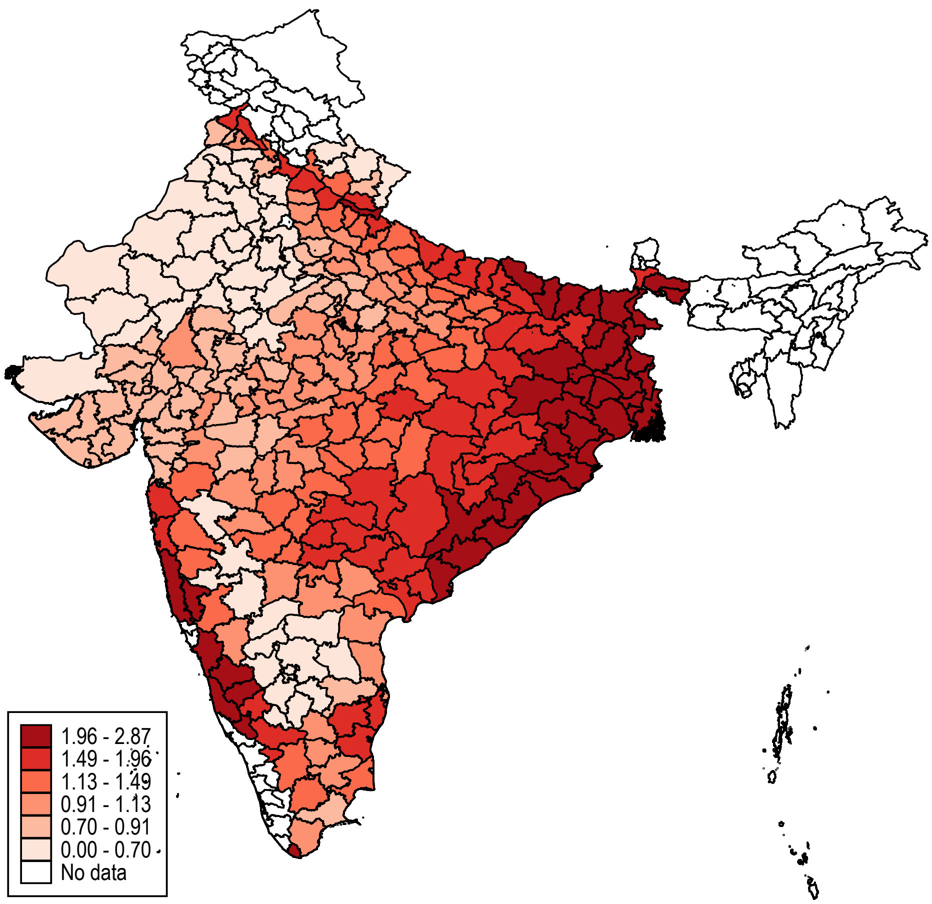
Source: FAO: GAEZ-v4

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



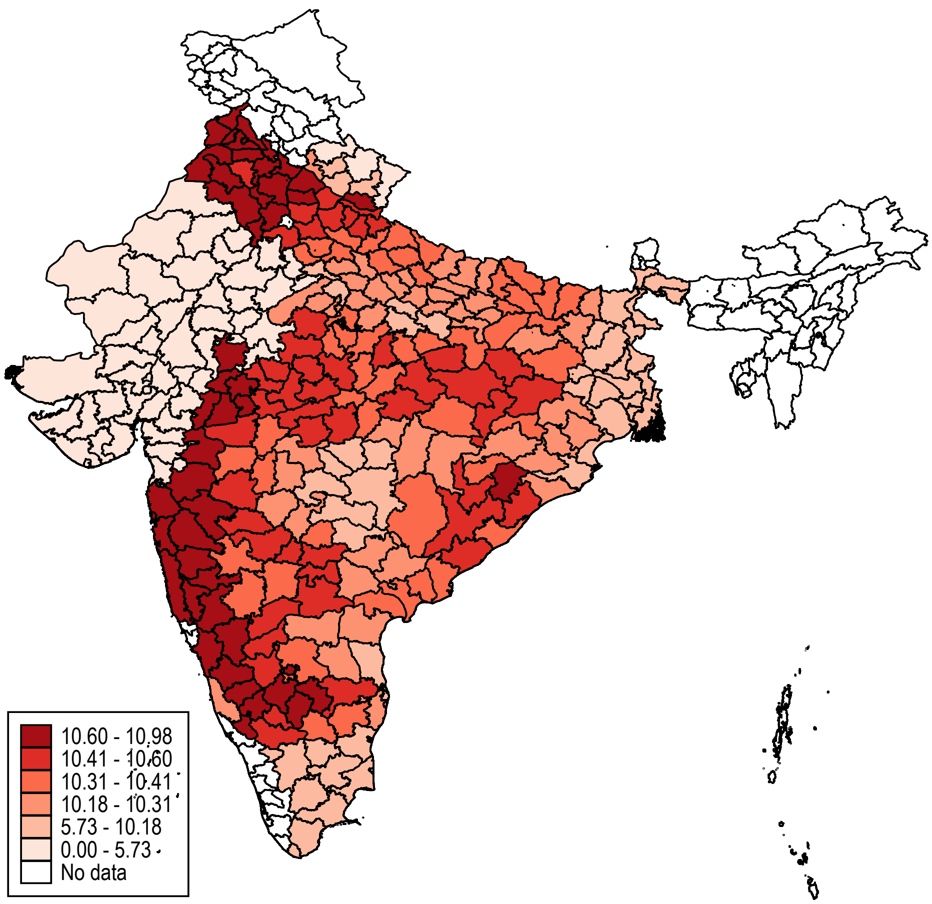
Source: FAO: GAEZ-v4

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



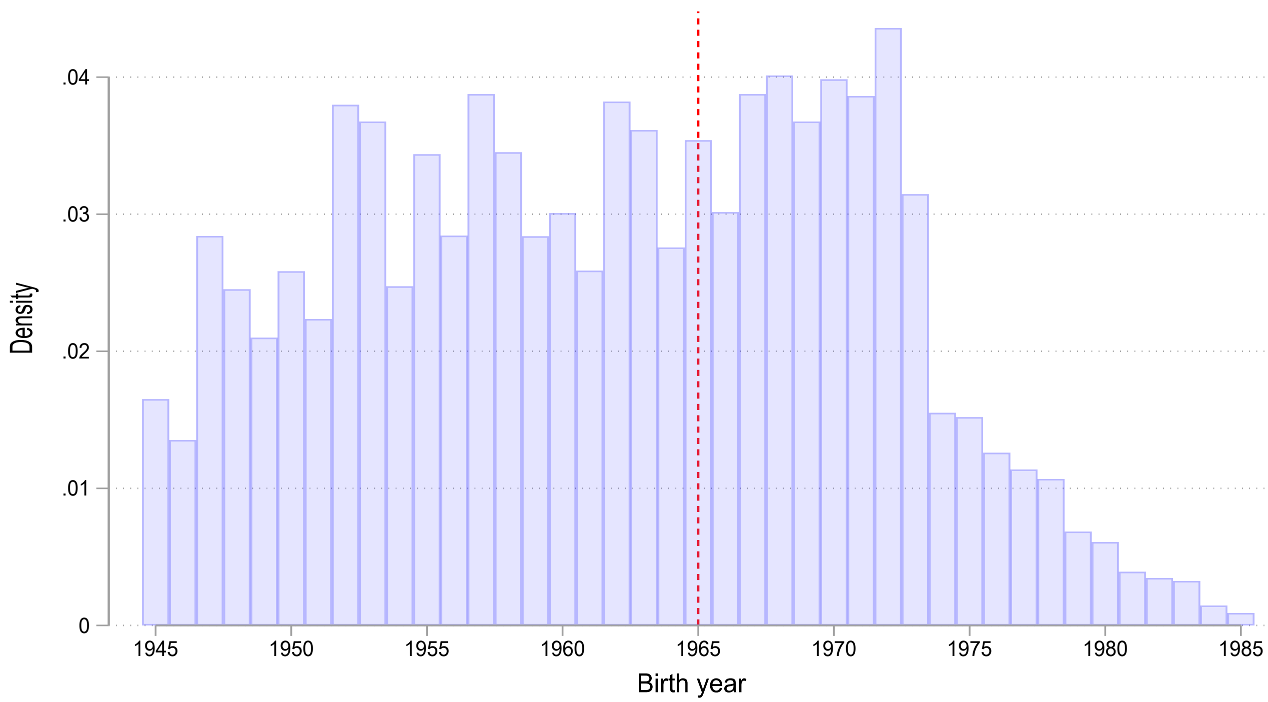
Source: FAO: GAEZ-v4

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

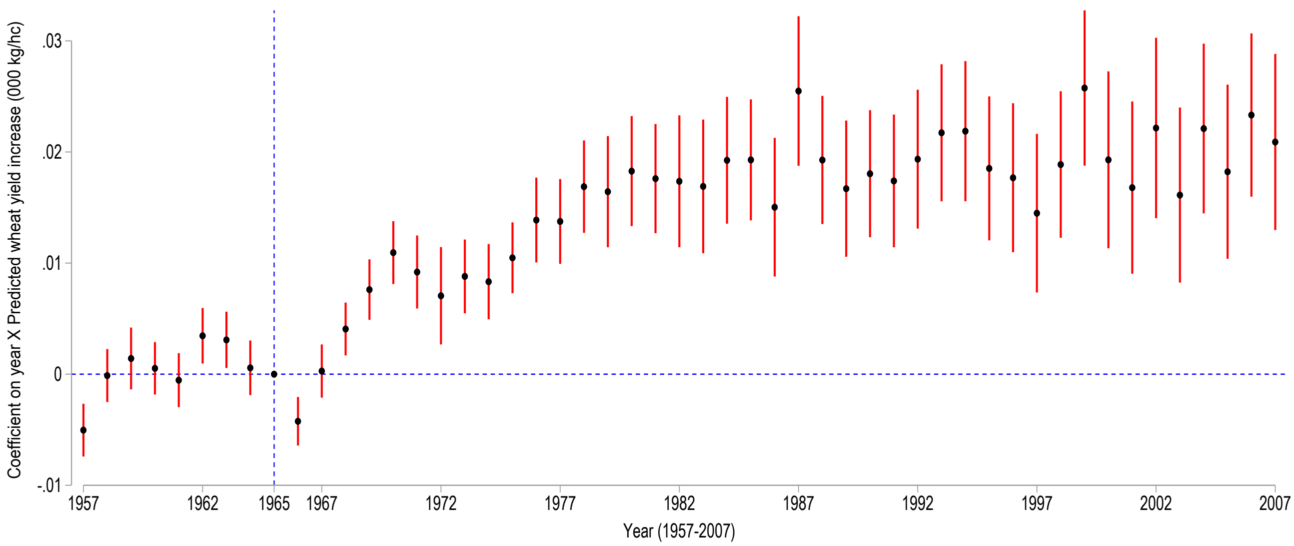
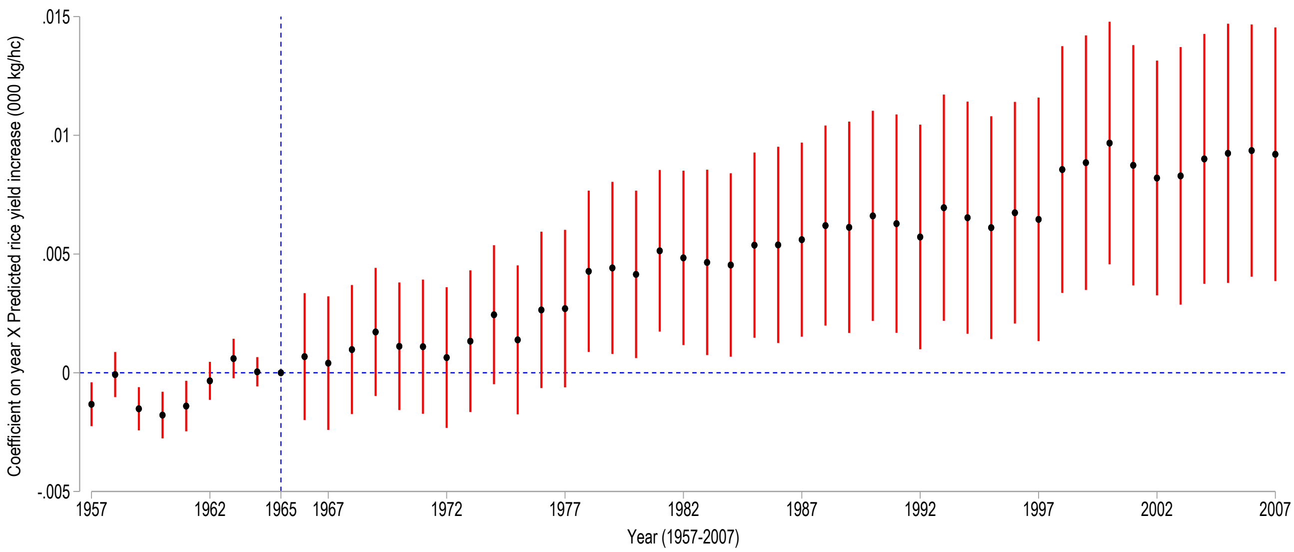
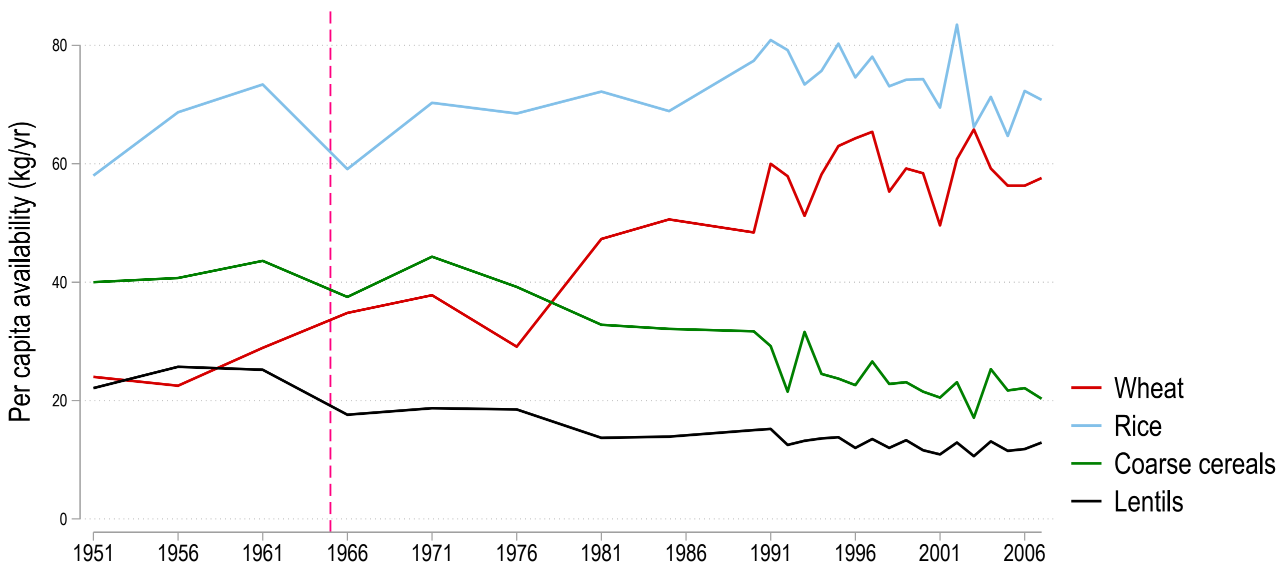


Figure A.9: Share of area under rice in total cultivated area over time



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

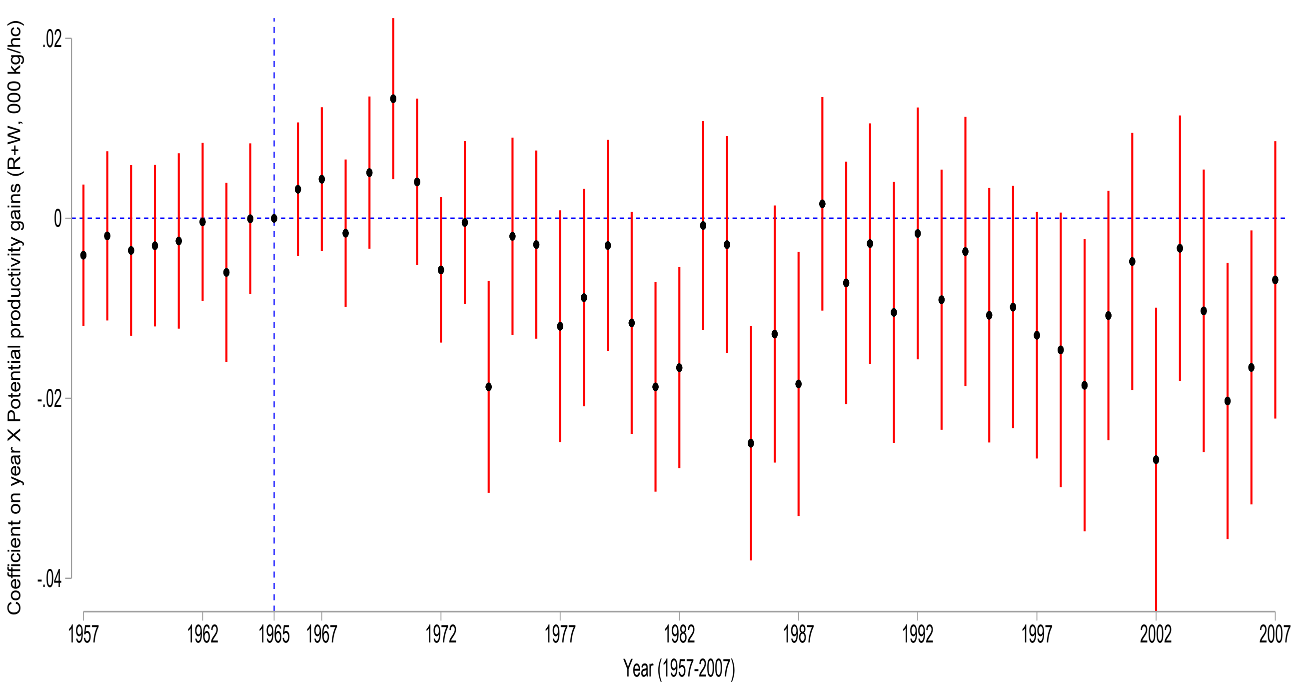


Figure A.12: Event study estimates of vitamin B2 per calorie produced

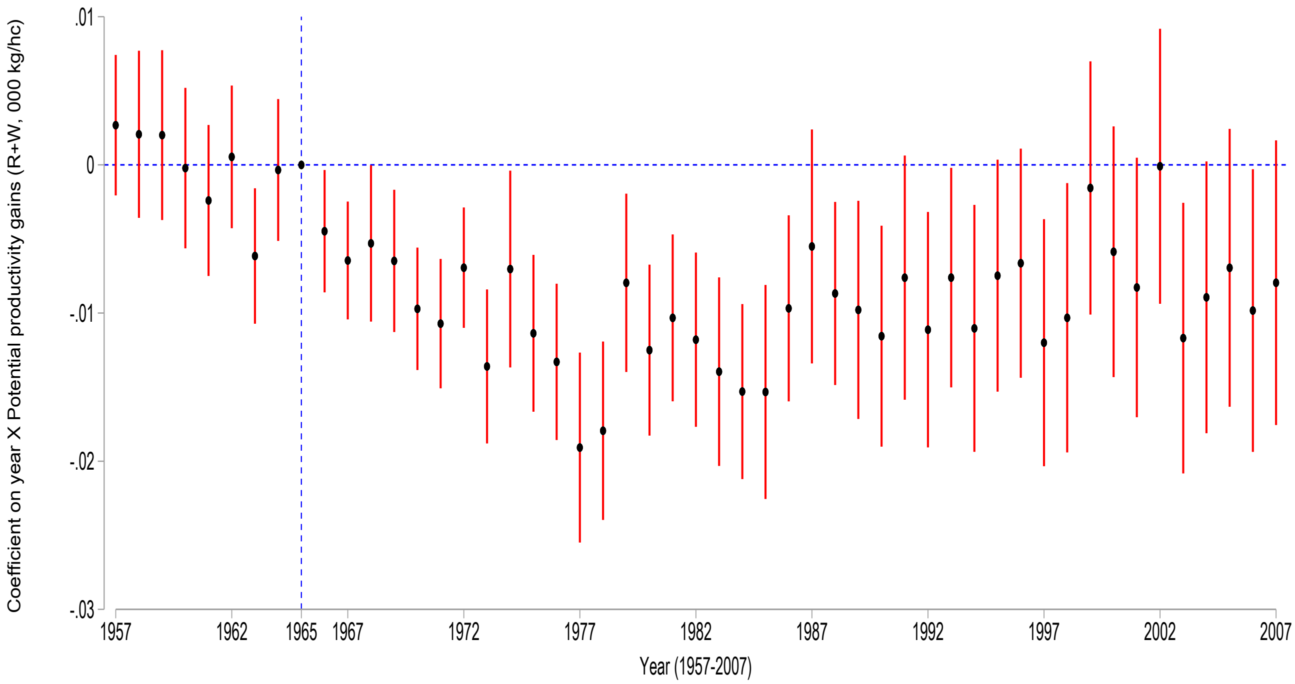
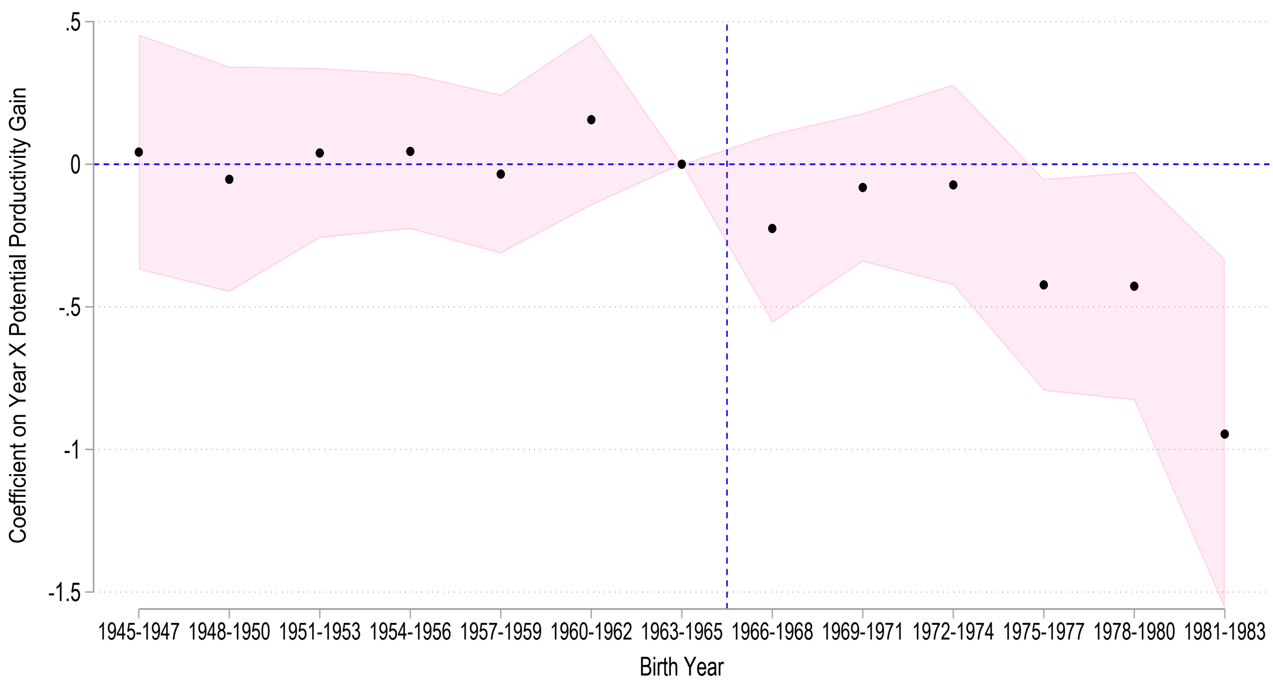
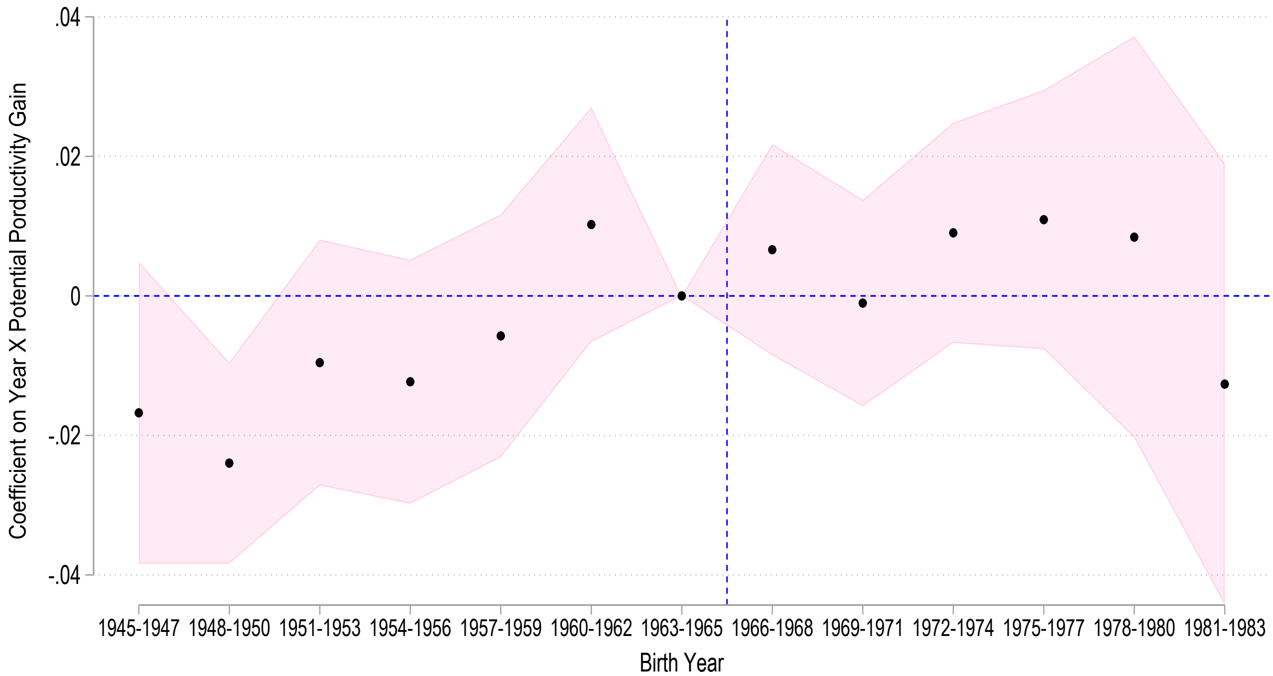


Figure A.13: Event study estimates of the effect of potential productivity gains on height



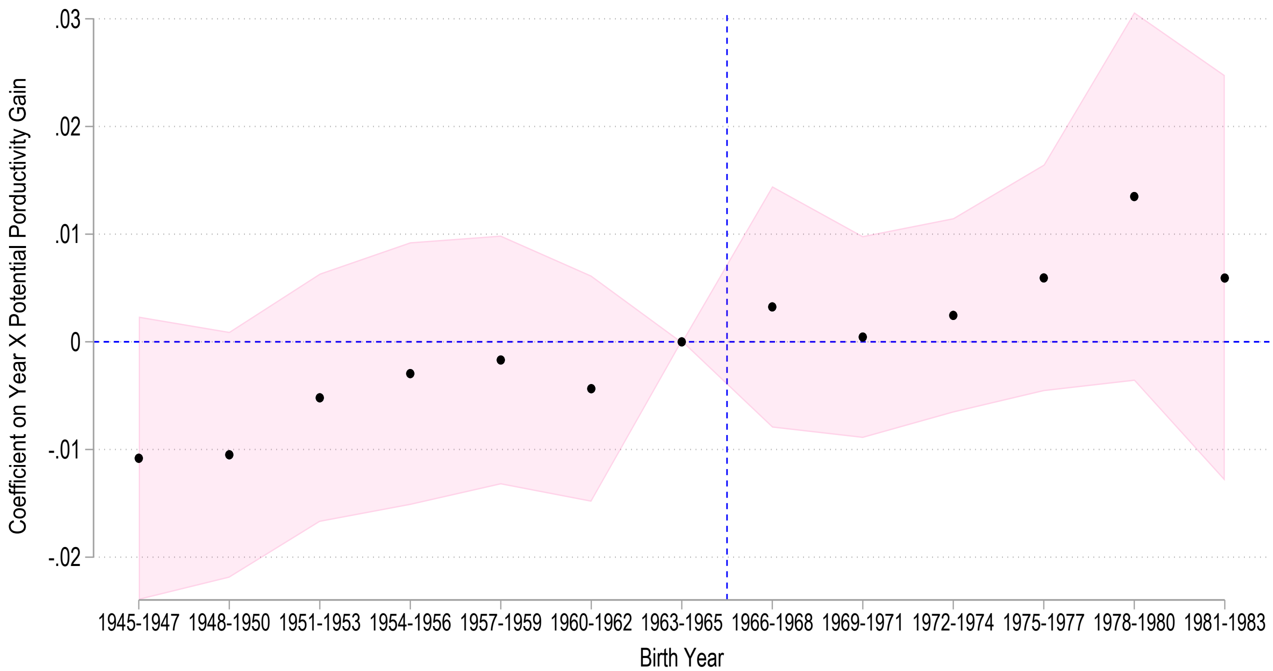
Notes: The figure plots the coefficients from estimating an event-study model (equation 5) using height as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation 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



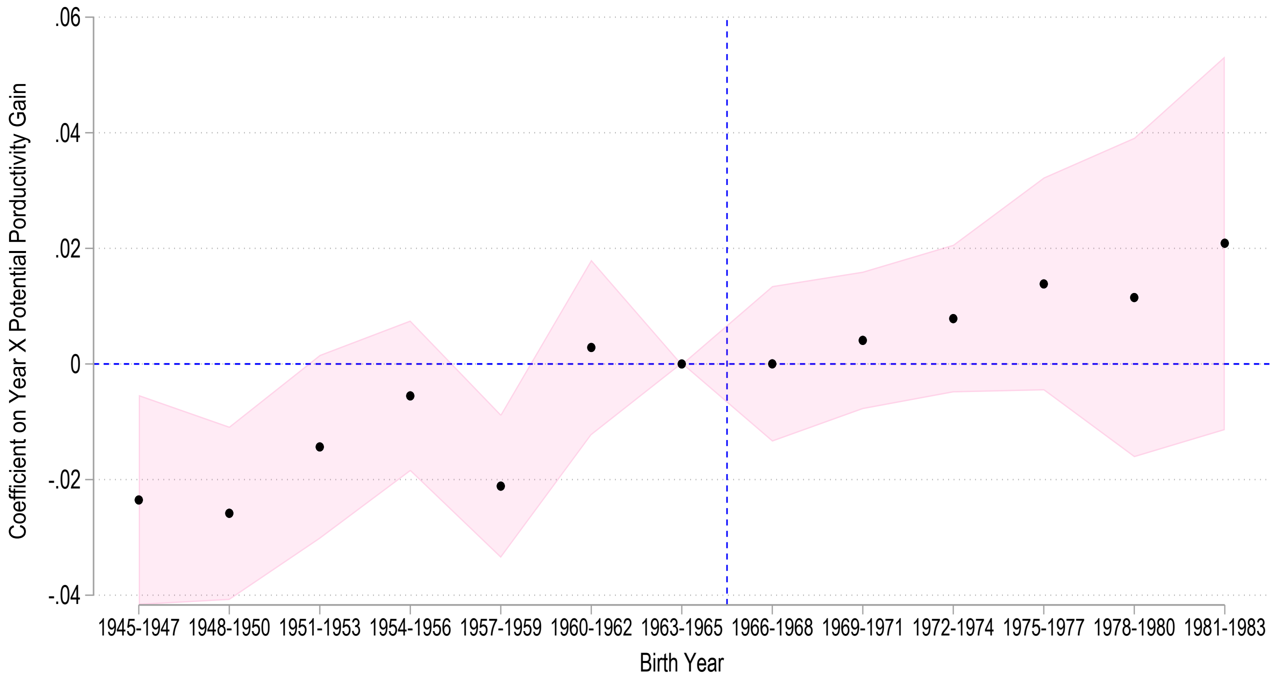
Notes: The figure plots the coefficients from estimating an event-study model (equation 5) using metabolic syndrome indexas the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer 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



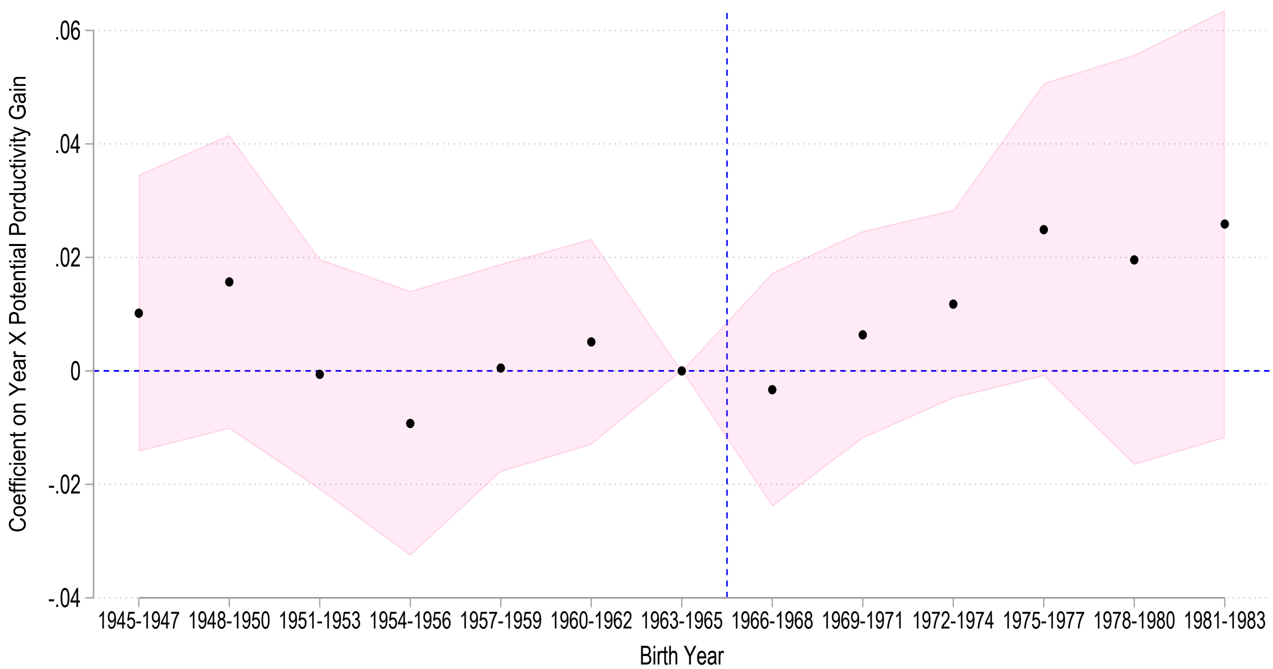
Notes: The figure plots the coefficients from estimating an event-study model (equation 5) using diabetes as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, precipitation 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



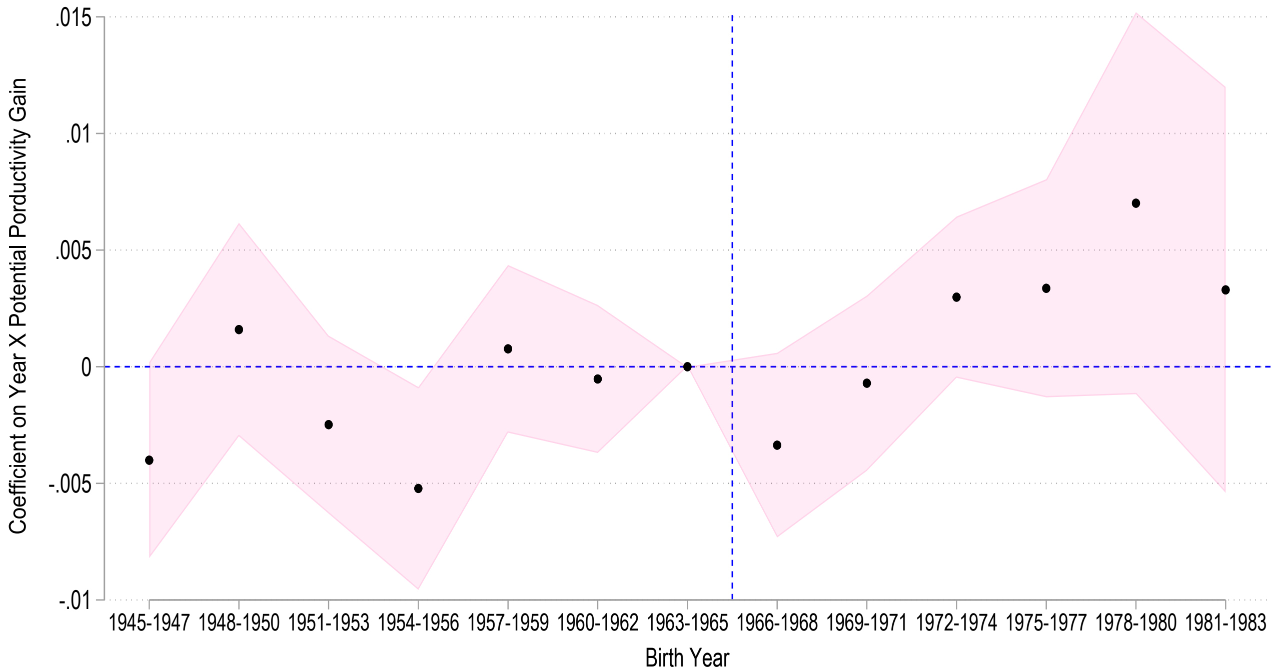
Notes: The figure plots the coefficients from estimating an event-study model (equation 5) using hypertension as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district, year fixed effects and ditstrict controls: total fertilizer exposure, 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 5) 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 5) 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 of potential productivity gains on height stunting

	Height Stunting	
	(1)	(2)
ProdGain × 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.2: 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.3: 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 4). 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.4: 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 4). 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.5: 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.6: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain × 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.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 × 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 4). 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.8: 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}	0.005	-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 4). 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.9: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.032*	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 4). 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.10: 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.11: 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 4). 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.12: 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 4). 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.13: 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 4). 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.14: Effect of potential productivity gains on height

	Height (cms)
	(1)
ProdGain × 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.15: 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 × 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 4). 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.16: 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}	0.015	-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 4). 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.17: Effect of potential productivity gains on cognitive imbalance

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × 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 4). 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.18: Rural-urban heterogeneity analysis: effect of potential productivity gains on height

	Height (cms)	
	(1)	(2)
ProdGain × Post^{1965}	-0.208***	-0.193***
	(0.073)	(0.074)
Born in rural area=1 × ProdGain × 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.19: Rural-urban heterogeneity analysis: effect of potential productivity gains on metabolic syndrome index

	Metabolic S Index	Components					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		BMI	WH-Ratio	Hypertension	Diabetes	Chronic Heart	Cholestrol
ProdGain × 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 × ProdGain × 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 4). 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.20: Rural-urban heterogeniety 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	0.002	-0.001	0.006^{*}
	(0.007)	(0.001)	(0.004)	(0.003)
Born in rural area=1 × ProdGain × $Post^{1965}$	-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 4). 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.21: Rural-urban heterogeniety analysis: effect of potential productivity gains on motor deficit

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × $Post^{1965}$	0.037^{**}	0.016^{*}	0.004
	(0.017)	(0.008)	(0.005)
Born in rural area=1 × ProdGain × $Post^{1965}$	-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 4). 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.22: 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.23: 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 4). 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.24: 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.25: 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.

Table A.26: HYV Adoption and Nutrient Intake: IV Estimates

	Agrochemical Health Risk	Components		
	(1)	(2) Respiratory	(3) Urogenital	(4) Cancer
ProdGain $\times$ Post^{1965}	-0.003	0.000	-0.002	-0.000
	(0.005)	(0.002)	(0.002)	(0.001)
Rural=1 $\times$ ProdGain $\times$ Post^{1965}	0.004*	0.001*	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.000)
Observations	29416	29416	29416	29416
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.	-0.019	0.043	0.052	0.006

Notes: This table presents the relationship between hyv adoption and nutrient intake. The regression include household socio-economic controls. State fixed effects are included. Standard errors are clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.