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 and malnutrition, with the underlying causes not fully understood. Nutritional imbalances could be significant contributors to these challenges, potentially stemming from agricultural transformations that focus on maximizing caloric production over nutritional adequacy. In this context, I examine the unanticipated effects of Green Revolution technologies, particularly the introduction of high-yielding varieties (HYVs) of rice and wheat in 1966, on crop diversity, nutrition, and long-term health outcomes. I use a difference-in-differences framework by using time variation from the Green Revolution's introduction and district-level variation in potential productivity gains from transitioning to HYVs, based on climatic characteristics. Districts with higher potential productivity gains for wheat and rice experienced greater HYV adoption, reduced crop diversity, lower lentil and millet production, and decreased availability of protein and micronutrients in the post-Green Revolution period. Individuals exposed to the Green Revolution in early childhood tend to be shorter and have higher rates of metabolic syndrome. These results suggest that early childhood nutritional declines can more than fully offset the long-term health benefits of concurrent income gains.

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1. Introduction

Despite significant economic growth in recent decades, malnutrition remains a 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, and neurological disorders (Siddique et al., 2021; Meenakshi, 2016; Pingali et al., 2017; Thow et al., 2016).Although qualitative studies suggest nutritional changes may be driving these shifts, empirical evidence remains limited (Shankar et al., 2017; Popkin et al., 2001; Shetty, 2002).

One hypothesis for these health challenges stems from the agricultural advancements of the 1960s, which prioritized caloric sufficiency by enhancing the production of energy-rich crops like rice and wheat, overlooking the importance of nutritional adequacy (Pinstrup-Andersen and Hazell, 1985). This agricultural transformation, particularly in India from 1965 onwards, led to the adoption of high-yielding varieties (HYVs), irrigation technologies and extensive agrochemical use, improving food security and productivity (Evenson and Gollin, eds, 2003; Pingali, 2012). While this movement effectively addressed caloric undernutrition, experts increasingly argue that the the focus on rice and wheat may have marginalized crop diversity, including essential nutrients from crops like lentils and millets, potentially contributing to emerging health issues linked to dietary changes(Shiva, 1991; Pingali et al., 2019). Historical evidence also indicate that interstate agricultural trade restrictions and limited market integration tied regional crop production to local consumption patterns (Dasgupta, 1983; Chand, 1999). In India, where plant foods form the backbone of the diet, changes in crop production patterns may have significant implications for nutrition and health.[2] Yet, empirical evidence on the Green Revolution's long-term health impacts, particularly through changes in crop diversity, remains limited. Sekhri and Shastry (2024) provide the first evidence on the long-term health impacts of the Green Revolution, showing that individuals born post-Green Revolution and residing in groundwater-rich districts during adulthood are more likely to develop diabetes, with dietary habits potentially driving these effects. However, the broader health impacts—shaped by changes in crop diversity, availability of consumption crops, and overall nutrition in a setting of market inefficiencies—remain scarce in evidence. Examining health implications is also difficult due to the lack of birth district data for individuals born before and after the Green Revolution, and the absence of long-term data to trace health effects into adulthood.

In this paper, I address this gap by exploring three main questions: How did Green Revolution adoption impact crop diversity, and affected the production of nutrient-rich consumption crops? Did the increase in caloric availability reduce the availability of proteins and micronutrients? Finally, using a new dataset that resolves the limitations of birth district data and long-term health tracking, what are the effects on long-term health for individuals exposed to the Green Revolution during early childhood,

[1]Despite India's economic growth exceeding 6% annually from 1992 to 2005, stunting declined by only 0.6 percentage points per year, reflecting a non-significant improvement in height compared to the substantial increases observed in Western countries (Tarozzi, 2008; Floud et al., 2011).

[2]According to the National Consumption Survey (1991), Hopper (1999) notes that India's wealthiest consume up to 14 grams of meat and over 400 grams of milk per day, but still derive 60% of their protein from plant sources. Among lower-income groups, who consume as little as 1 gram of meat and less than 10 grams of milk daily, 96% of their protein intake comes from plants.

particularly in terms of growth, metabolic health, cognitive abilities, and motor function?

To answer these questions, I use a difference-in-differences (DiD) framework, leveraging exogenous variation in Green Revolution exposure across districts and over time. The introduction of the Green Revolution in India in 1966 is the source of time variation. Anecdotal evidence further suggests that HYV wheat and rice were adopted more extensively in regions with greater expected productivity gains, driven by favorable agro-climatic characteristics (Das, 1999). Consequently, I rely on district-level differences in potential productivity gains from climatic suitability as the source of cross-sectional variation. To quantify these gains, I use Food and Agriculture Organization (FAO) models that estimate the maximum potential crop yields for wheat and rice at a grid cell level of 9.25 km x 9.25 km. These models assess climatic suitability and categorize yield estimates by input levels (high or low) and irrigation conditions (irrigated or rainfed). Specifically, potential yields under low input and rainfed conditions represent the use of traditional varieties, while those under high input and irrigated conditions reflect the potential yields achievable through HYV adoption. I aggregate these potential yield estimates to the district level and then calculate the difference between the two measures to create a metric of potential productivity gains for wheat and rice.[3]

I examine the effects of the Green Revolution on crop diversity, nutrient-rich crop production, and nutritional availability using a longitudinal district-level dataset that spans 270 districts (approximately 80% of India's districts at the time) from 1957 to 2007. This dataset provides information on agricultural production, total cropped area for 21 major and minor crops, area under HYVs of wheat and rice, alongside fertilizer use and socio-economic variables. Using the difference-in-differences strategy, I first show that districts with higher potential productivity gains from wheat and rice have higher HYV adoption rates. I then find that these potential gains lead to a decline in crop diversity, from an average of 5 crops to 2 crops in districts with the highest gains, indicating a shift from a diverse cropping system to near-monoculture. Next, I use an event study analysis to test for the parallel trends assumption. Before the Green Revolution in 1966, districts with different levels of potential productivity gains exhibited parallel pre-trends in crop diversity. However, post-Green Revolution, districts with higher potential gains experienced a gradual and sustained decline in crop diversity, a pattern consistent across different measures of crop diversity. Additionally, I find that this decline is primarily driven by reduced cultivation and production of barley, pearl millet, chickpea, pigeon pea, minor pulses, and groundnut. These millets and legumes, which are richer in protein, fiber, and essential micronutrients like iron, zinc, and folate compared to rice and wheat, could provide a more balanced nutrient profile, suggesting that their decline may affect nutrition security (Longvah, 2017).

To explore this, I convert crop production data into caloric and nutrient equivalents using the National Food Composition Table (2017). Leveraging the same difference-in-differences design employed to estimate the effects on crop diversity and production of different crops, I examine the impact of potential productivity gains on both calorie availability and nutrient availability per calorie. The analysis reveals that exposure to higher potential productivity gains boost calorie production by 20% and increases carbohydrate supply per calorie by 0.6%. Conversely, protein supply per calorie declines by

[3] My identification strategy draws from recent work in economic development and history, using exogenous variation in agro-ecological suitability to study technology adoption (Nunn and Qian, 2011; Bustos et al., 2016; Bartik et al., 2019; Moscona, 2023).

3%, while iron, folate, and zinc decrease by 2%, 9%, and 2%, respectively. These results suggest that while increased calorie availability might benefit health, the decline in nutrient density might limit the achievement of nutritional adequacy, potentially leading to negative health consequences.[4]

Given the effects on calorie and nutrient availability, I examine how these shifts may impact health outcomes. Previous work on understanding the long-term health might suffer from misclassifying early-life exposure, as they rely on district of residence in adulthood. I overcome this limitation by using individual-level data from the 2017 Longitudinal Aging Study in India (LASI), which includes measures of physical, metabolic, cognitive, and motor health, as well as district and year of birth for individuals born between 1945 and 1985. This allows me to link individuals to district-level Green Revolution exposure based on their birth year and district, isolating the effect between those exposed to the Green Revolution during early childhood (birth to age one) and those born before its onset. I use difference-in-differences and event-study models to analyze health outcomes for those born shortly before and after the Green Revolution's introduction in 1966, in districts with varying levels of potential productivity gains. This approach builds on evidence of the 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 in utero and early childhood, leading to stunted growth, metabolic disorders, and impaired development (Mehta et al., 2002; Stein et al., 2003; Christian and Stewart, 2010; Rees, 2019).[5]

I estimate the effects of the Green Revolution exposure on adult height, metabolic syndrome, cognitive decline, and motor skill deficits. My results indicate that cohorts born after the Green Revolution, exposed to higher potential productivity gains in early childhood, are significantly shorter and have a higher incidence of metabolic syndrome than those born earlier. Specifically, in districts where potential productivity gains increase by one standard deviation, cohorts born after the Green Revolution are, on average, 0.3 cm shorter than those born earlier. This finding is particularly noteworthy, considering that average heights in India increased by only 4 cm during the 20th century (NCD-RisC, 2016). Notably, the 0.3 cm gap represents approximately 8% of the height difference between individuals from the poorest and wealthiest quintiles, 8% of the disparity associated with education (none to more than 15 years), and 10% of the height difference between scheduled and general caste group (Perkins et al., 2011). Additionally, these cohorts exhibit a 0.014 standard deviation increase in metabolic syndrome, attributed to a 3 percentage point rise in hypertension and a 1.5 percentage point increase in diabetes compared to their earlier counterparts. While I observe a rise in cognitive imbalance and motor func-

[4]Historical evidence from qualitative accounts indicates that between the 1950s and 1980s, the growth in agricultural production—at an annual rate of 2.6%, outpacing population growth of 2%—helped arrest the decline in food consumption among the lowest-income groups (Hopper, 1999; Evenson, 1986). However, this improvement was not observed across other income groups, where consumption remained largely stable. Additionally, anecdotal evidence indicates a shift in dietary patterns, with increasing dependence on wheat and rice, potentially displacing more nutrient-dense foods like lentils and millets (Evenson, 1986).

[5]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 diminished (Sekhri and Shastry, 2024).

tion deficits, these effects are weakly significant. The negative consequences for health are striking, especially considering the marked increase in caloric production in these areas. It seems that if caloric intake did increase, nutritional deficiencies would still negate the potential health benefits associated with that increase.

A natural concern is that the observed effects on health outcomes may be influenced by non-nutrition-related factors associated with the Green Revolution, such as increased agrochemical exposure. I provide suggestive evidence that this channel is not significantly influencing the results in three ways. First, I include fertilizer exposure at the birth district and birth-year level in my preferred specifications. Second, although fertilizer use is controlled for, pesticide exposure remains a concern since HYV adoption typically involves higher pesticide use, especially impacting rural areas. To investigate this further, I compare survey respondents born in rural and urban areas to examine the impact of these factors on health outcomes, finding that the negative effects of the Green Revolution on height are smaller in rural areas. This suggests that pesticide exposure may not be the main factor. Furthermore, I find no evidence that individuals born in rural areas after the Green Revolution have a higher incidence of metabolic syndrome, cognitive deficits, or motor function deficits compared to urban counterparts in districts with greater potential gains. Lastly, I create an indicator for the sowing months, which are also the peak months for fertilizer and pesticide application, and perform a heterogeneity analysis to assess whether individuals born during these months exhibit different outcomes. I do not find any significant differences in the results.

Another concern is selection effects, as Bharadwaj et al. (2020) find that the Green Revolution led to a decline in infant mortality rates, potentially altering the health composition of surviving cohorts and influencing the observed health outcomes. I conduct a bounding exercise following Lee (2009) to address potential selection effects, trimming the sample to exclude individuals whose survival is influenced by the Green Revolution. The results from the lower and upper bounds are very similar to my preferred estimates, suggesting that any selection effects due to mortality are minimal. To ensure the robustness of my findings, I conduct a battery of checks addressing alternative explanations, including differential healthcare access, lifestyle changes, adult health behaviors, and spillover or composition effects. The results remain consistent across these specifications.

To this point, I show that the Green Revolution has implications for crop diversity, nutrient availability, and health outcomes. A logical inference from these findings is that reduced crop diversity negatively affects health by altering patterns of food consumption. I next explore the relationship between patterns of food consumption and health outcomes. Given the scarcity of individual-level dietary data from the study period, I provide suggestive evidence linking dietary habits to adverse health outcomes using LASI household consumption data. I find that individuals born in high-potential gain districts after the Green Revolution reside in households that consume more rice per capita from ration shops and experience higher rates of hypertension and diabetes, particularly in households with a larger proportion of cereal expenditures compared to their counterparts born before the Green Revolution. Additionally, using data from a nationally representative Household Consumption Expenditure Survey conducted in 1999-2000, I find that men born post-Green Revolution in high-potential gain districts live in households with lower-than-recommended micronutrient intake, a gap more pronounced in rural areas.

My study on the Green Revolution in India during the 1960s highlights its long-term impacts and connects this history to the current Green Revolution 2.0, which promotes a modern agricultural system focused on environmental responsibility and production. This approach aligns with the Sustainable Development Goals, particularly those of zero hunger and responsible production and consumption. I show that Green Revolution technologies affected crop diversity, especially through the reduction of lentil and millet production. While caloric availability increased, protein and micronutrient availability declined. Additionally, I find that individuals exposed to the Green Revolution in early childhood face challenges such as shorter stature, higher rates of metabolic syndrome, and deficits in motor function. These findings emphasize the importance of enhancing crop diversity and nutrition while promoting responsible agricultural practices to improve health outcomes in the future.

This paper makes two 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 on the Green Revolution has primarily examined its economic effects concerning population growth, income, and employment, or assessed its impact 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) report 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) examine the long-term effects of Green Revolution exposure on diabetes in India, using historical aquifer presence as an exogenous determinant of HYV adoption. They find that cohorts born after the Green Revolution and residing in aquifer-rich districts in adulthood face a higher diabetes risk, attributing this to dietary shifts, including risk being pronounced in rice-eating states and declining pulse production in these districts.

I extend and improve on this line of inquiry in several ways. First, using a different identification strategy based on agroclimatic suitability, I replicate their findings on diabetes and expand the analysis to include broader health outcomes, including multiple metabolic health parameters, as well as adult height, motor skills, and cognitive outcomes. Second, I examine how the Green Revolution affected crop diversity and nutritional crops, specifically analyzing its impact on the availability of protein, iron, zinc, folate, and vitamins linked to various health outcomes. Third, by using the LASI 2017-18 data and assigning treatment based on district of birth, I avoid potential misplacement of exposure by district of residence in adulthood. The data also allows me to track individuals into later life, from ages 30-50, which is advantageous compared to previous study focusing on post-treatment cohorts aged 20-40, as health issues like metabolic disorders, cognitive decline, and motor skill deterioration often become more apparent in later years. Additionally, unlike the previous study, I can better assess gender-based heterogeneity since my data includes district-of-birth identifiers and tracks health outcomes also for women later in life. My analysis supports the medical hypothesis that males and females respond differently to early childhood or in utero nutritional changes, with males being more susceptible to long-term health impacts.

Second, my paper contributes to the broader literature on how economic and nutritional resources during in-utero and childhood affects 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 The 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. Before 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, supported by global donors, were established, including the International Rice Research Institute and the International Centre for Maize and Wheat Improvement, which eventually coalesced into the Consultative Group for International Agricultural Research. This combination of public and private sector initiatives spurred a rapid increase in the development of high-yielding crop varieties (Evenson and Gollin, eds, 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 increased the yields of rice from approximately 1 ton per hectare to 5 tons per hectare (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 (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. However, the adoption and impact of the Green Revolution technologies were not uniform across India. The success of HYV adoption was heavily dependent on agroecological suitability, infrastructure, and local conditions (Evenson and Gollin, 2003). Northwestern states like Punjab, Haryana, and Uttar Pradesh reaped significant benefits due to their favorable climate, well-established irrigation systems, and infrastructure that supported intensive agriculture. In contrast, regions like eastern India, which faced challenges such as limited irrigation, poor infrastructure, and environmental conditions that made crops vulnerable to diseases, pests, and abiotic stresses, were slower to adopt HYV 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). Building on this, I will use regional variation in agro-climatic suitability to isolate exogenous variation in HYV adoption, to be able to estimate causal effects on crop diversity, nutritional availability, and health outcomes.

2.2 Potential Nutritional Implications of Green Revolution

The Green Revolution likely reshaped India's dietary landscape by driving shifts in crop production that influenced food consumption patterns. To understand the scope of these changes, it's helpful to consider the traditional Indian diet, which has long been predominantly plant-based. Between 1950 and 1990, plant foods provided roughly 94% of India's total energy supply and 85% of its protein intake (Hopper, 1999). Typical Indian meals often center on cereal, such as millet, wheat, or rice, complemented by pulses or curried vegetables. Nutrient-dense staples like lentils and millets are rich in protein, fiber, and essential micronutrients such as iron, zinc, and folate, in contrast to the relatively lower nutrient profile of wheat and rice. Given this heavy reliance on plant–based foods, the widespread adoption of HYV wheat and rice may have altered traditional diets through several interconnected mechanisms, including income effects, reductions in crop diversity, and changes in relative food prices, potentially undermining nutrition security in some regions.

In districts with favorable climate and infrastructure, the adoption of HYVs significantly boosted agricultural productivity, leading to higher farm incomes (Foster and Rosenzweig, 1996). According to Bennett's Law in agricultural economics, as incomes grow, households often shift from staple cereals to more diverse, nutrient-dense diets. Yet, this shift depends on the availability of diverse food options. Limited technological advances and inadequate market support for nutrient-rich crops like millets, lentils, and vegetables restrict their supply, making it challenging for households to improve their diets even with higher incomes (Pretty and Bharucha, 2014; Pingali, 2019; Pingali et al., 2017).[6] Moreover, if wheat and rice are considered normal goods, rising incomes would likely further increase their consumption.

Beyond income effects, HYV adoption might have influenced diets by reshaping agricultural pro-

[6] Appendix Figure A.5 shows the per capita availability of rice, wheat, pulses, and coarse cereals in India from 1956-2007, revealing increased wheat and rice supplies but declining pulses and coarse cereals.

duction patterns. In India, local consumption has traditionally mirrored agricultural production due to market imperfections, such as high transaction costs, limited market integration, and state-level trade restrictions (Panikar, 1980; Dasgupta, 1983; Chand, 1999). While economic theory suggests that efficient markets should allow production specialization regardless of local consumption needs, these imperfections often directly link agricultural output to dietary patterns (Evenson, 1986). Historical data shows a strong correlation between per capita agricultural production and calorie intake, especially from cereals, indicating that shifts in local production can significantly impact consumption.[7] Experts suggest that promoting HYVs has intensified wheat and rice cultivation, likely reducing crop diversity and limiting access to nutrient-dense foods like pulses and millets, with potential long-term nutritional consequences (Shiva, 1991; Pingali et al., 2017, 2019).[8]

The decline in crop diversity might have influenced relative prices, with market imperfections contributing to price disparities across regions and affecting crop affordability. Panikar (1980) observed that inter-state differences in cereal prices widened from 1960 to 1975, with the coefficient of variation in average retail cereal prices rising from 15.2% in 1961-62 to 23.6% by 1973-74. If HYV adoption decreased the production of lentils and millets, their prices likely increase in regions dominated by wheat and rice, limiting access to these nutrient-rich foods. Meanwhile, the relative decline in prices for wheat and rice may shift dietary preferences toward these energy-dense options.[9] Although cheaper wheat and rice could theoretically free up household income for more varied foods, households may still rely on a narrower range of nutrient-poor staples, potentially impacting long-term nutritional outcomes.

Social, cultural, and labor dynamics might also have influenced shifts in dietary preferences. Rice and wheat have long symbolized social mobility and refinement, and as they became more accessible, people may have increasingly consumed these foods to align with cultural perceptions of status. In contrast, millets were often regarded as "inferior goods" associated with economic hardship (Berg, 1970; Finnis, 2008; Deaton and Drèze, 2009).[10] The increased supply and relative decline in the prices of rice and wheat might have further encouraged this shift. Additionally, the labor-intensive processing of millets, requiring tasks like husking and grinding, made them less convenient. In contrast, rice and wheat benefited from government-supported milling expansions in the 1960s and 1970s, offering ready-to-use flour and shorter cooking times. The lack of similar processing for millets until the late 1990s likely reinforced the preference for rice and wheat (Finnis, 2008).

Changes in the Nutrient Profile of the Indian Diet: So far, I have outlined how the Green Revolution might have shifted dietary patterns in India. Now, how might these changes have influenced the nutritional composition of diets? Nutritionally, according to India Food Composition Table (2017), wheat, coarse cereals or millets contain about 9-12% protein, whereas rice provides approximately 7-

[7] Panikar (1980) found that in the early 1970s, inter-state calorie intake differences correlated strongly with per capita cereal output, with coefficients of 0.7 in 1961-62 and 0.7 in 1971-74.

[8] From 1972-73 to 2011-12, per capita sorghum consumption dropped from 8.5 kg to 1.6 kg in urban areas and from 19.2 kg to 2.4 kg in rural areas. Pearl millet intake also declined, from 11.5 kg to 0.97 kg in rural areas and from 4 kg to 2.8 kg in urban areas (Rao et al., 2010; Basavaraj et al., 2010).

[9] For instance, in Hapur district, Uttar Pradesh, the real price of wheat decreased from 0.7 per 100g in 1965 to 0.4 in 1981, while chickpea rose from 0.4 to 0.7 during the same period (Meenakshi et al., 1986).

[10] Historically, food choices reflected class divides: wealthier households preferred "fine" cereals like rice and wheat, while millets were considered "coarse" grains for the poor (Umanath et al., 2018).

8%. In contrast, lentils have a higher protein content of 20-25% per 100 grams. However, it is essential to consider not only the quantity but also the quality of protein, which is determined by the essential amino acid profile. Lentils are commonly consumed alongside cereals or millets, making their combined protein interactions vital for achieving a balanced amino acid intake and protein consumption.[11] Specifically, lentils provide around 45 mg of essential amino acids per gram, while rice offers 16.5 mg, millets deliver approximately 12-15 mg, and wheat has 9.5 mg. Micronutrient content further differentiates these crops. Lentils are particularly nutrient-dense, providing 4-6 mg of iron, 100-200 µg of folate, 2-4 mg of zinc, and 45-70 mg of calcium per 100 grams. Coarse cereals and millets are also rich in essential nutrients, containing on average 2-6 mg of iron, 30-40 µg of folate, 1-3 mg of zinc, and 27-30 mg of calcium per 100 grams.[12] In comparison, wheat approximately supplies 4 mg of iron, 29 µg of folate, 2 mg of zinc, and 30 mg of calcium per 100 grams, while rice offers 1 mg of iron, 10 µg of folate, 1.5 mg of zinc, and 8 mg of calcium per 100 grams[13]. Additionally, coarse cereals and millets provide more fiber content and have a lower glycemic index than both wheat and rice.

In a cereal-pulse diet, ideally, 20-25% of protein should come from lentils to ensure amino acid adequacy and protein retention. Before the 1960s, around 60% of the rural population fell below this level, rising to over 90% in the early 1980s. In urban areas, only 10% were deficient in lentil intake in the early 1950s, but this figure reached 40% subsequently (Evenson, 1986). Similarly, Hopper (1999) highlights that between 1960 and 1995, pulse availability fell from 63 to 36 grams per day, even though wheat and rice supplies increased, it led to a loss of 634 mg of amino acids daily. Furthermore, coarse cereals consumption declined significantly, dropping from 35% to 5% in rural areas and from 17% to 3% in urban areas between 1960 and 2011, potentially leading to lower intake of essential nutrients like iron and folate (DeFries et al., 2018).

While this anecdotal evidence suggests a dietary shift post-Green Revolution, the long-term health effects remain uncertain. Increased income and changes in relative prices may encourage dietary diversification and higher caloric intake; however, potential nutritional deficiencies in protein and micronutrients could emerge from a variety of economic, social, and labor dynamics.

2.3 In Utero Adverse Nutritional Exposure and Long-Term Health Effects

Early-life nutrition is crucial for development and lifelong health. After the Green Revolution, diets might have improved in calories but may have introduced nutrient imbalances, leaving individuals vulnerable to insufficient protein and micronutrients. These deficiencies during in-utero stages could contribute to long-term health issues, as maternal nutrition significantly influences children's linear growth, cardiovascular and cognitive health. The concept of "developmental origins of adult disease" emerged from 1980s research in the United Kingdom, highlighting significant correlations between ma-

[11] Pulse proteins complement cereal proteins by providing high lysine levels, which cereals lack. Conversely, cereals supply methionine and cystine, amino acids that pulse typically have in low quantities. This combination improves the overall quality of the protein (Meenakshi et al., 1986).

[12] Finger millet offers a notably higher 364 mg of calcium per 100 grams.

[13] While rice contains lower levels of these nutrients compared to wheat, its bioaccessibility is significantly higher where bioaccessibility refers to the proportion of nutrients in food that becomes available for absorption during digestion (Hemalatha et al., 2007)

ternal undernutrition, low birth weight, and increased risks of metabolic syndrome later in life (Barker, 1994). Early nutritional deficits can lead to epigenetic and physiological changes that program the body to conserve energy and store fat in response to nutrient scarcity—a phenomenon known as the "thrifty phenotype". However, when food becomes abundant later in life, the thrifty phenotype may heighten the risk of metabolic disorders, including cardiovascular issues. While this adaptation is relevant in nutrient-deprived contexts, it appears less applicable to populations born after the Green Revolution, where caloric supply significantly increased (Sekhri and Shastry, 2024).

For post-Green Revolution cohorts, poor "quality" of nutrition, such as protein imbalance, may explain health issues. Observational and experimental studies indicate that insufficient protein intake during pregnancy can result in long-term effects, including impaired cognitive and motor development, shorter stature, and increased risks of obesity, hypertension, glucose intolerance, and type II diabetes (Desai and Hales, 1997; Stocker et al., 2005; Hoppe et al., 2004). Despite increased caloric supply, many diets may have remained heavily reliant on carbohydrates and deficient in essential proteins. Micronutrient deficiencies also play a critical role in shaping long-term health. Research shows that inadequate folate, zinc, iron, and calcium during crucial developmental periods can lead to epigenetic changes, predisposing individuals to chronic conditions, reduced linear growth, cognitive difficulties, and heightened risks of neuropsychiatric disorders (Christian and Stewart, 2010; Zou et al., 2021; Bailey et al., 2015; Gernand et al., 2016; Martorell, 2017).

3. Data

3.1 Adoption of HYV and Crop Diversity

To analyze the impact of the Green Revolution on crop diversity and crop production, I require data on crop area and production before and after its implementation. Indian Agricultural and Climate Data (IACD) and International Crops Research Institute for the Semi-Arid Tropics–District Level Data (ICRISAT) provide district-level annual information on the area planted with HYV of wheat and rice, total cropped area (hectares), production, and yield (kg per hectare) across five major and 19 minor crops, representing 95% of India's agricultural output. Covering 266 districts (80% of all districts) from 13 states in India from 1957 to 2007, the datasets also include socioeconomic and agro-ecological variables.[14] Figures 1 and 2 show that HYV wheat and rice adoption reached 90% by the 1990s, with significant yield increases following the Green Revolution.

To compute the 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 the crop diversity index, I calculate the Shannon Diversity Index. It 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 the Shannon Index is $[0, ln(n)]$. In my dataset, the range is [0.06, 2.55].[15] Appendix Figures 3 and 4 show the average district-

[14]The 13 states included, based on the 1961 census, are Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

[15]I also compute alternative measures for robustness checks: The Simpson Diversity Index, which is measured as $1 - \sum_{i=1}^{n} p_i^2$, and I also use a simple measure, the number of unique crop types planted.

level HYV adoption and crop diversity during the period 1960–2007. To analyze nutrient availability, I calculate the caloric and nutrient equivalents of each crop by multiplying production values by their caloric and nutrient content from the National Food Composition Table (2017).

3.2 Potential Yield of Wheat and Rice

For cross-sectional variation in exposure to the Green Revolution, I construct a metric of potential productivity gains from transitioning to HYV technologies for rice and wheat, leveraging district-level agro-climatic suitability. The metric is derived from theoretical models of maximum potential crop yields as outlined by the Food and Agriculture Organization's Global Agro-Ecological Zones (FAO GAEZ). These models estimate yield potentials based on controlled experimental parameters rather than actual agricultural inputs and outputs, taking into account factors such as temperature, solar radiation, and moisture within specific grid cells. Key crop characteristics incorporated into the model include growth cycle duration (from emergence to maturity), yield formation period, maximum photosynthesis rates at prevailing temperatures, leaf area index during peak growth, harvest index, crop adaptability, sensitivity of growth cycle length to heat, and water requirements at different developmental stages, along with yield response to water stress.

The FAO provides this data in a 9.25 km x 9.25 km raster grid, with each cell representing the maximum potential yields for specific crops in that area. The data is available under two scenarios: "low" and "high" input levels, and, "rainfed" and "irrigated" conditions. In low-input systems, traditional farming practices are assumed, relying on traditional varieties and labor-intensive methods without fertilizers, pesticides, or conservation measures. Conversely, high-input systems are characterized by market-oriented practices that utilize high-yielding varieties, mechanization where feasible, reduced labor requirements, and optimal applications of fertilizers and chemicals for pest, disease, and weed control.

I aggregate the grid cell-level data to compute the average potential yield for rice and wheat under both low-input, rainfed conditions, and high-input, irrigated conditions for each district (the calculation of the metric is detailed in the following section).[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.3a-A.3d.[17]

3.3 Individual Health Outcomes

To analyze health outcomes, I require data on individuals' district of birth, year of birth, and health outcomes for those born both before and after the Green Revolution. The Longitudinal Ageing Survey

[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 of 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).

of India is a nationally representative dataset that includes information on individuals aged 45 and older, along with their spouses (including those under 45). It encompasses 42,000 individuals born between 1945 and 1985, sampled from 2,440 villages and towns based on the 2011 census. The dataset provides comprehensive information on demographics, household economic status, chronic and symptom-based health conditions, functional and mental health, biomarkers, employment, life satisfaction, childhood health, and family medical history. Crucially, it contains data on the district of birth. I match LASI data with FAO data based on district of birth rather than residence. This process provides individual-level health outcomes for people born in 251 districts.[18,19]

I use the following responses from LASI: (i) Height measured in cms, (ii) self-reported incidence of hypertension, diabetes, chronic heart disease, high cholesterol, (iii) self-reported neurological or psychiatric problems including Alzheimer's, Parkinson's, epilepsy, depression, anxiety, schizophrenia, and bipolar disorder. I create two measures of obesity: (i) Body Mass Index (BMI) criteria and, (ii) Waist-Hip circumference ratio (WHR).[20] I also create metrics for cognitive functioning and motor balance. I measure cognitive functioning using the Mini-Mental State Examination attributes from the LASI data, with two binary variables: (i) poor cognitive functioning (MMSE score ≤ 15), where the sample mean is 15, and (ii) mild cognitive impairment (MMSE score ≤ 19), the cutoff used in the medical literature.[21] Motor balance is assessed using (i) grip strength deficit, with an indicator set to 1 if grip strength (measured in kg) is below the age and gender-specific cutoff, and (ii) balance deficit, defined as 1 if an individual's score on a timed walk and tandem balance test is below the cutoff.

To address the numerous outcome variables, I follow the approach by Kling et al. (2007), Hoynes et al. (2016), and Sekhri and Shastry (2024) by constructing summary standardized indices that aggregate information from various outcomes. Specifically, I construct four indices: the metabolic syndrome index (comprising measures of hypertension, diabetes, obesity, chronic heart conditions, and high cholesterol), the cognitive imbalance index (encompassing neurological disorders and cognitive metrics), and the motor deficit index (including grip strength and balance deficits). Aggregating measures within a domain, such as metabolic syndrome, enhances statistical power. The summary index is computed as the average of standardized z-scores for each component, where each z-score is derived by subtracting the mean from the value and dividing by the standard deviation. Higher index values correspond to worse health outcomes. Table 1 provides summary statistics for the demographics and health outcomes of individuals in the LASI data.

[18] 26% of the individuals either migrated to another district.

[19] 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. Appendix Figure A.4 shows that there is no issue of age heaping in the LASI data.

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

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

3.4 Household Consumption

To understand the effect of the Green Revolution on actual consumption, I use data from the 1999-2000 round of cross-sectional survey on household consumption expenditure conducted by the National Sample Survey Organization. The survey encompasses around 70,000 rural households across 8,000 villages and 45,000 urban households from 4,500 urban blocks within the 13 states under analysis. It captures household expenditures and quantities for each food item consumed in the past 30 days, including homegrown 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. I calculate household-level caloric and nutritional intake by multiplying the quantity consumed by the caloric or nutrient content of each food item (based on estimates from the India Food Composition Table, 2017, National Institute of Nutrition, India). The surveys also provide information on household demographics and characteristics. I use this data to calculate the nutrition adequacy ratio, which is defined as the ratio of the actual intake of a nutrient to the recommended intake in a household. I calculate the recommended intake using the Indian Council of Medical Research guidelines for different age groups and sexes, considering household composition by age and sex.

3.5 Additional Controls

Data on population density, the share of the urban population, the share of service sector employment, and the share of the literate population in the Indian districts comes from the 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 (2012). For the healthcare availability, I use the data on the number of primary healthcare centers from Iyer (2010).

4. Empirical Strategy

To estimate the causal effects of the Green Revolution, I leverage agro-climatic variation in wheat and rice suitability. In particular, following Moscona (2023), I create a metric of average potential productivity gains for wheat and rice and link it to district-level agricultural and health data to analyze effects on crop diversity, production, nutritional availability, and health. This section explains the construction of the productivity gains metric and outlines the estimation equations.

Potential Productivity Gains

FAO follows a two-step methodology to determine agricultural potential. First, it assesses whether a grid-cell is agroclimatically suitable for crop cultivation. Then, for suitable grid-cells, FAO models calculate potential yields under different input and water availability conditions based on the degree of climatic suitability. The areas with optimal conditions have higher potential yield compared to those with sub-optimal conditions. I measure potential benefits from transitioning to HYV by calculating the difference in average potential productivity between high-input, irrigated farming systems (associated with HYV technologies) and low-input, rainfed farming (typical of pre-Green Revolution agriculture) across climatically suitable grid-cells within each district.

Since wheat and rice are complementary seasonal crops—wheat grown in the Rabi (winter) season and rice in the Kharif (summer/monsoon) season—farmers can cultivate both crops within the same year in districts that are agroclimatically suitable for both crops. In districts suitable for both crops, the potential productivity gains from transitioning to HYVs will be higher as farmers can adopt improved varieties for both wheat and rice cultivation. In contrast, districts suitable for only one crop will still benefit from HYV adoption, but their total potential gains will be lower compared to districts suitable for both crops.

To understand this , we can think of the difference in potential productivity for crop $c \in \{\text{wheat, rice}\}$ in district d as given by:

$$\Delta P_d^c = \underbrace{\left(\frac{1}{n_d} \sum_{g=1}^{n_d} \mathbf{I}_g^c P_g^{H_c} \right)}_{P_d^{H_c}} - \underbrace{\left(\frac{1}{n_d} \sum_{g=1}^{n_d} \mathbf{I}_g^c P_g^{L_c} \right)}_{P_d^{L_c}}$$

where n_d is the number of grid cells in district d, $\mathbf{I}_g^c$ is an indicator variable that equals 1 if grid cell g is agroclimatically suitable for crop c cultivation (as determined by the FAO), $P_g^{H_c}$ is the potential productivity of crop c in grid cell g under high input and irrigated conditions, and $P_g^{L_c}$ is the potential productivity of crop c in grid cell g under low input and rainfed conditions. ΔP_d^c represents the difference in average potential productivity for crop c in district d. Finally, I construct a measure of average potential productivity gains in district d as follows:

$$\text{ProdGain}_d = \frac{\Delta P_d^w + \Delta P_d^r}{2}$$

where ΔP_d^w and ΔP_d^r measure the intensity of potential gains for wheat and rice in the district d.

Estimating Equations

I will estimate changes in outcomes between the pre- and post-1966 periods across districts likely to adopt Green Revolution technologies. My empirical strategy uses two variations: (i) the timing of the Green Revolution's start in 1966 and (ii) cross-district differences in potential productivity gains. I use the following difference-in-differences (DID) model:

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

where $Y_{d,t}$ is the outcome of interest. The main outcome variables are (i) share of HYV wheat and rice area, (ii) crop diversity, (iii) area under different crops, (iv) production of different crops, and (v) calorie and nutrient availability per calorie in district d in year t. Post_t^{1965} is an indicator for years post 1965, $X_{d,t}$ are either time varying district characteristics– average precipitation and temperature– or baseline (1957) district characteristics interacted with year fixed effects (described when introduced in the analysis). δ_d and τ_t are district of birth and year of birth fixed effects. I cluster standard errors at the district level. The coefficient of interest in equation 1 is ψ, which is the estimated effect of potential productivity gains on hyv adoption, crop diversity, area and production of different crops and nutrient availability. Equation 1 examines the average effects of the potential productivity gains on the outcomes of interest. I also estimate time-varying effects of the Green Revolution using the following specification:

$$Y_{d,t} = \sum_{n=1957}^{1964} \psi_n^{pre} \left(\text{ProdGain\_wr}_d \times \gamma_n\right) + \sum_{n=1966}^{2007} \psi_n^{post} \left(\text{ProdGain\_wr}_d \times \gamma_n\right) + \beta' X_{d,t} + \delta_d + \tau_t + \varepsilon_{d,t} \tag{2}$$

where $Y_{d,t}$ is the outcome of interest, γ_n denotes year dummies, ψ_n^{pre} and ψ_n^{post} are coefficients of interest for the pre- and post-1966 periods. These coefficients represent the differential annual relationship between potential productivity gains and the outcome, measured relative to the omitted year, 1965. This approach captures effects that can grow, diminish, or change non-monotonically over time. Estimates of ψ_n^{pre} close to zero would support the identifying assumption of parallel trends by indicating no differential trends in the relationship between potential productivity gains and the outcome prior to the Green Revolution.

Health Outcomes

I estimate a similar model using individual-level data on health outcomes, applying a difference-in-differences approach. I compare health outcomes among individuals born in the same district who, depending on their birth year, were exposed to varying potential gains from the district's transition to HYV wheat and rice, while controlling for unobserved health shocks that may vary by birth year. Specifically, I estimate the following:

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

where $Y_{i,d,t}$ is the health outcome of interest for individual i, born in district d and year t; $X_{i,d,t}^1$ are individual level controls for gender, religion, caste and whether the individual was born in a rural area, $X_{d,t}^2$ represents district-by- year-of-birth controls, such as fertilizer exposure, mean rainfall, and temperature, to isolate the specific effect from broader impacts related to early childhood fertilizer exposure and weather conditions. δ_d and τ_t are district and year of birth fixed effects. I cluster standard errors at the district-of-birth level.[22]

The identification strategy in equation 3 differs from many previous design-based studies in the fetal origins literature. Typically, natural experiments like famines or disease outbreaks are short-term—they occur and then end. However, exposure to the Green Revolution is continuous. Once the Green Revolution technologies are introduced in a district, they remain in use and do not end. In studies that focus on short-term impacts, such as maternal exposure and infant mortality (e.g. Bharadwaj et al. (2020); Von Der Goltz et al. (2020); Brainerd and Menon (2014)), treatment is often binary, com-

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

paring periods before and after an intervention. In contrast, my study deals with prolonged exposure throughout childhood. For example, I cannot observe a birth cohort exposed only in early childhood but not in later years. Instead, I compare cohorts with added exposure early in life, conditional on exposure later in childhood. To illustrate this, suppose an individual's health can be modeled as a function of exposure to Green Revolution technologies during two time periods: early childhood (period 1) and later life (period 2). My analysis compares cohorts born just before and after the Green Revolution in areas with higher potential productivity gains, relative to those in areas with lower gains. The treatment group, born after the Green Revolution, experiences full exposure in both periods, while the comparison group, born before, has no exposure in early childhood but the same exposure later. This comparison help me to isolate the impact of early-life exposure.

I also use an event-study model to estimate the time-varying effects of potential productivity gains, controlling for birth year, district of birth, and district-level covariates. This event study model allows me to examine how the effect of potential exposure to the Green Revolution varies by age of exposure. I group birth cohorts into three-year intervals to mitigate the issue of sparse observations at the district-year level, ensuring robust estimates. I track how differences evolve across districts, using individuals born between 1963 and 1965 as the reference group, similar to Sekhri and Shastry (2024). For this analysis, I define six three-year periods for pre-1966 cohorts (ranging from 1945 to 1962) and six three-year periods for post-1966 cohorts (spanning from 1966 to 1983). I estimate the following equation:

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

where γ_n represents the birth cohort dummies, ψ_n^{pre} and ψ_n^{post} are the coefficients of interest for the pre- and post-1966 cohorts, respectively. Estimates of ψ_n^{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.

Note that this framework differs from a typical event-study framework where control cohorts are not exposed to the treatment. In my study, however, everyone will eventually be exposed to the Green Revolution, but the key difference lies in the age at which individuals are exposed. Those born before the Green Revolution are exposed at progressively older ages, while those born after 1966 are exposed from birth. This allows me to examine how the timing of exposure—whether in utero, early childhood, or later—affects health outcomes.

5. Results

5.1 Adoption of high-yielding varieties of wheat and rice

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

Although HYVs were not introduced in India until 1966, I estimate equation 2 to explore the relationship between potential productivity gains and the share of HYV adoption for wheat and rice in the periods following 1965. Figure 6 shows the trend in HYV adoption in total cultivated area over time. Before 1966, the area planted with HYVs was zero across all districts, indicating no differential trends before the Green Revolution. I conduct a similar regression from 1957 to 2007 to analyze the relationship between potential productivity gains and the share of area under wheat and rice. Since direct data on HYV adoption before 1966 is unavailable, this regression serves as a proxy for pre-existing trends. Appendix Figures A.6 and A.7 show no significant pre-trends.

It is important to note that potential productivity gains are based on theoretical models of potential yield, calculated using climatic characteristics. As a result, these values are unlikely to be influenced by endogenous factors or observed production patterns. Furthermore, I have shown in Table 2 that the relationship between potential productivity gains and the share of HYV adoption is not affected by district-level variation in initial characteristics.

5.2 Effect on crop diversity

After establishing that potential productivity gains strongly predict HYV adoption, I examine their relationship with crop diversity. Table 3 estimates equation 1, analyzing the effect of potential productivity gains on crop diversity, measured by the Shannon Diversity Index. Column (1) shows a strong negative relationship between crop diversity and potential productivity gains, with only fixed effects included. In Column (2), I add controls for initial geographical and socio-economic characteristics, and the negative relationship remains strong in both magnitude and statistical significance. Assuming an equal distribution of crops, a mean Shannon Diversity Index of 1.5 equates to 4.5 crops. A one standard deviation increase in potential productivity gains (1.26 tonnes per hectare) reduces crop diversity from 4.5 to 3.8 crops. In districts with full average potential gains (8 tonnes per hectare), crop diversity decreases from 4.5 to 2.2 crops. Additionally, a simpler analysis using the number of crops as the dependent variable (Appendix Table A.1) shows that full potential productivity gains (8 tonnes per hectare) would reduce crop diversity from 4.3 to 2 crops.[23]

[23] 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 4.5. A 1 s.d. increase in potential productivity gains leads to a

To further validate the empirical strategy, I estimate the flexible specification in equation 2. In favor of the parallel trends assumption, I find no evidence of pre-trends in crop diversity before 1966 (Figure 7). This absence suggests that, without the Green Revolution, districts with different levels of exposure to productivity gains would have followed similar trajectories in crop diversity. Post-1966, however, I observe a significant decline in crop diversity, with this effect intensifying over time. This pattern is likely driven by increasing impacts of potential gains on HYV adoption, as shown in Figure 6.

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

Building on the analysis of the overall decline in crop diversity, I now examine which specific crops experienced a reduction in cultivated area. Different crops are grown in distinct seasons, and potential productivity gains from adopting HYV wheat and rice may drive crop substitution. For example, in the Rabi (winter) season, wheat, barley, and chickpeas are cultivated. As productivity gains from wheat increase, farmers might shift land from barley and chickpeas to wheat. Similarly, in the Kharif (monsoon) season, crops like rice, maize, pearl millet, and sorghum are grown. Higher potential gains from rice could lead to more land allocated for rice at the expense of other Kharif crops. To examine this, I estimate an equation similar to 1, using the cultivated area of different consumption crops as the dependent variables.[24] This analysis will highlight the shifts in crop cultivation, revealing which crops were most impacted by the likely adoption of HYV wheat and rice. Figure 8 shows the effect on the area under different consumption crops. The results indicate that as potential productivity gains increase, the area dedicated to wheat and rice expands, while the area for barley, pearl millet, chickpea, minor pulses, and groundnut decreases.

Declining Crop Diversity and Shifts in Production

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

Despite the decline in production of certain consumption crops, imports may have been sufficient to sustain overall availability. Although district-level data on imports and exports is unavailable, ICRISAT provides national-level data on per capita availability (kg/year), which is defined as production plus net imports per capita, for the period from 1951 to 2006. This data is categorized into four main groups: wheat, rice, coarse cereals (including millets, maize, and sorghum), and lentils. I analyze

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

[24]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 the following crops: Barley, finger millet, maize, sorghum, pearl millet, chickpea, pigeon pea, minor pulses, potatoes, onion, groundnut, soybean, wheat, and rice.

trends in per capita availability for these food groups to assess the impact of production and imports on overall availability. Appendix Figure A.5 shows that while per capita availability of wheat and rice has increased, availability of lentils and coarse cereals has decreased, reinforcing the argument that access to diverse food options is becoming increasingly limited.

Availability of Nutrients

Lentils, barley, and pearl millet provide unique nutritional benefits compared to wheat and rice, particularly in terms of protein content and essential micronutrients. To assess the impact of these production changes on caloric and nutritional availability, I run equation 1 using the caloric and nutrient equivalents of the sum of these consumption crops as the dependent variables. I emphasize nutrient availability per calorie because the total number of calories an individual consumes might not change significantly, as people tend to consume a relatively fixed amount of calories. However, nutrient intake is directly influenced by the nutrient density of those calories. If there is a decline in the supply of nutrients per calorie, nutrient intake might decrease substantially if there is a minimal increase in calorie intake. Even if calorie intake increases from a very low baseline, if the decline in the supply of nutrients per calorie is substantial, the resulting increase in nutrient intake because of higher calorie intake may not be significant or could even lead to an overall decline in nutrient availability. Hence, this approach allows me to critically assess the potential impacts on diet quality amid changes in caloric availability.

Table 4 presents the result from the estimation. The results show that exposure to higher potential productivity gains increased calorie production by 20% and carbohydrate supply per thousand calories by 0.6% relative to the mean. However, protein supply per thousand calories declined by 3% relative to the mean, while iron decreased by 2%, folate by 9%, and zinc by 2%. Concerning protein and micronutrients, the results suggest that moving from no productivity gains to the highest potential gains would result in a decrease in protein supply of approximately 8.42 grams per 1,000 calories. Additionally, iron would decline by 1.44 mg, folate by 75.75 µg, zinc by 0.74 mg, and vitamin B2 by 0.07 mg per 1,000 calories.

As a back-of-the-envelope calculation for protein, consider an individual in 1961 who consumed the recommended intake of 2150 calories and 45 grams of protein, as specified by the Indian Council of Medical Research in the 1960s; then the protein density achieved would be approximately 20.93 grams per 1000 calories. After the Green Revolution, if calorie intake remains adequate but dietary composition shifts, the protein density could decrease to 12.51 grams per 1000 calories, resulting in a total protein consumption of only 25 grams. This represents a significant decline in protein intake of 44%.[25] In another scenario, where the baseline calorie intake is inadequate at 1700 calories but protein intake remains at 45 grams, the protein density would yield 26.47 grams per 1000 calories. If calorie intake subsequently increases to 2150 calories, maintaining the original protein density would result in an intake of 57 grams, which exceeds the recommended amount. However, if the protein density declines by 8 grams per 1000 calories, the new protein intake would be approximately 40

[25] A similar analysis for iron indicates that with an adequate baseline intake of 30 mg at a calorie level of 2150, post-Green Revolution, iron consumption would decline by 10%. For folate, with a pre-Green Revolution intake of 200 µg at an adequate level of 2150 calories, the folate intake would decline by 80% after the Green Revolution.

grams, indicating a decrease in overall protein consumption.

However, this analysis offers suggestive scenarios and results that warrant cautious interpretation. While the crops included in the calculation account for 70-80% of the average Indian diet, not all calories, protein, and micronutrients are derived from them. Furthermore, I have assumed a scenario where the shift occurs from minimal to maximum gains in potential productivity; consequently, the results may not reflect significant changes for districts with smaller increases.

I also estimate the coefficients from the flexible specification in equation 2 for each outcome variable related to calories and nutrients. Figures 10 -15 show the time-varying effects of potential productivity gains on calorie and nutrient availability per calorie. I find three key results: First, trends in all outcomes between the treatment and control groups were nearly identical before the Green Revolution, reinforcing the model's identifying assumption that, without the Green Revolution, caloric and nutrient outcomes would have followed similar trajectories. Second, following the Green Revolution, there is an increase in total calories and carbohydrates per calorie produced. Third, there is a decrease in protein, zinc, iron, and folate per calorie produced.

So far, I've provided evidence that potential productivity gains lead to increased adoption of HYV wheat and rice and a decrease in crop diversity, especially among nutrient-rich crops. This shift has reduced the availability of protein and essential micronutrients per calorie, which could have significant impacts on dietary quality and health outcomes. The next section will examine these potential health effects in detail.

5.3 Effect on Health Outcomes

In this section, I examine how exposure to potential productivity gains during infancy affects various health outcomes, using the early origins of the disease hypothesis as a framework. I first present evidence on impacts to height, metabolic syndrome, cognition, and motor skills, and then analyze placebo health outcomes to validate these findings.

Adult Height

Height provides a summary measure of the stock of nutritional investments made during an individual's early life and is associated with increased living standards life expectancy, and decreased mortality. Table 5 estimates equation (3) to analyze the relationship between potential productivity gains and height measured in cms. The first column includes individual controls, district, and year of birth fixed effects, and the second column also includes district controls for precipitation, temperature, and fertilizer exposure at the year of birth. In districts with a one standard deviation increase in potential productivity gains (1.4 tonnes per hectare), cohorts born after the Green Revolution are shorter by 0.3 cm compared to those born earlier. Similarly, cohorts born in districts with the highest potential productivity gains experienced a 1.2 cm reduction in height on average, relative to earlier birth cohorts from the same high-gain districts. The negative effect on height is particularly revealing, as it suggests that while wheat and rice may have provided sufficient calories, there was likely a shift away from protein- and micronutrient-rich foods toward a diet more reliant on wheat and rice, which are predominantly carbohydrate-rich. Empirical evidence demonstrates that malnutrition, particularly deficiencies in essential nutrients, can adversely affect fetal growth and development. Despite potential improvements in calorie intake, the adverse effects of nutritional deficiencies appear to have outweighed these gains, ultimately leading to a negative effect on height.

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

In India, average height has increased only modestly over the past century—women's height rose by 5 cm, from 147 cm to 152 cm, while men's height grew by just 3 cm, from 161 cm to 164 cm (NCD-RisC, 2016). Despite India outperforming many African countries in key development indicators, height disparities between the regions remain significant. Jayachandran and Pande (2017) highlight the role of gender-based birth-order differences and son-preferences in explaining these height gaps, particularly in India. My findings offer further evidence of persistent nutritional inadequacies that may contribute to these ongoing height disparities, pointing to another factor behind lower average Indian heights.

Table A.2 shows the result for the effect of potential productivity gains on adult stunting-an indicator variable defined as having a height lower than 2 standard deviations below the gender-specific average based on the Indian DHS 2004-05 data. While the estimates are positive, the effect is statistically insignificant. This suggests that the negative effects observed in the previous table may be concentrated in the upper portion of the height distribution, rather than at the lower end where stunting is typically defined.

Metabolic Syndrome

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

Table 6 shows the results of my analysis on how potential productivity gains affect the MSI and its components. It includes district-by-year-of-birth controls for precipitation, temperature, and fertilizer exposure along with the district-of-birth and year-of-birth fixed effects.[26] I find that potential productivity gains significantly impact the MSI, with a coefficient of 0.012, which is statistically significant at the 5% level. This coefficient indicates that in districts with a one standard deviation increase in potential productivity gains, cohorts born after the Green Revolution exhibit a significant increase in the MSI of 0.026 standard deviations compared to their earlier counterparts. I observe positive coefficients for all components of the MSI except chronic heart conditions. However, only the coefficients

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

for hypertension and diabetes are statistically significant. Specifically, in districts with a one standard deviation increase in potential productivity gains, cohorts born post-Green Revolution experience a 3 percentage point increase in the incidence of hypertension and a 1.5 percentage point increase in diabetes. My estimates align with Sekhri and Shastry (2024), who identified a 4 percentage point increase in diabetes prevalence among men born in groundwater-rich districts following the Green Revolution. In my analysis, males born post-1966 in districts with the highest potential productivity gains exhibit a 5 percentage point increase in diabetes prevalence and a 13 percentage point increase in hypertension incidence, relative to their counterparts.

Cognition and Motor Skills

Given that nutrient deficiencies can affect cognitive development and motor skills, I also examine the effects of potential productivity gains on cognitive imbalance and motor function deficit using the LASI data. Column 1 of Table 7 shows the effect on the cognitive imbalance index (CII). The CII is calculated as the equal-weighted average of the z-scores for three dichotomous variables: neurological disorder, cognitive score($<$15) and, cognitive score($<$19). Although the effect is positive, it is statistically insignificant. Column 2 shows the effect on neurological disorders, which is positive but also statistically insignificant.

Column 1 of Table 8 shows the effect on the motor deficit index (MDI). The MDI is calculated as the equal-weighted average of the z-scores for two dichotomous variables: grip strength deficit and balance deficit. The effect on the overall deficit is positive but statistically insignificant. Column 2 shows the effect on grip strength deficit, which is positive and statistically significant at 10%. Overall, the results suggest that potential productivity gains have a limited effect on cognitive imbalance and motor function deficit.

Placebo Health Outcomes

I analyze health outcomes unrelated to early childhood exposure as a placebo check. I evaluate the impact of potential productivity gains on the likelihood of experiencing physical injuries or disaster-related health risks. The results presented in Table A.37 indicate that there is no significant effect of potential productivity gains on these health risks.

Event Study Analysis

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

Appendix Figure A.10 shows the event-study estimates for the effect on height. There are two key findings. First, the pre-Green Revolution trends for treatment and control cohorts are nearly identical, reinforcing the identifying assumption—that in the absence of the Green Revolution, outcomes between the two groups would have evolved similarly. Second, following the Green Revolution, we observe a decline in height compared to the reference cohort. The transitional dynamics suggest that exposure to potential productivity gains from the Green Revolution between conception and age 1 leads to shorter height compared to exposure after age 1. Additionally, later post-period coefficients exhibit stronger effects, likely because HYV adoption increased over time, resulting in greater exposure to HYVs for those born in later years. In contrast, no negative effects are found for cohorts born before 1966, indicating minimal impact on height from exposure beginning after age 1.

Appendix Figures A.12 and A.13 show the event-study estimates for the effect on diabetes and hypertension. For diabetes, the trends between treatment and control cohorts before the Green Revolution are nearly identical. However, after 1966, there is an increase in diabetes incidence, suggesting that exposure to potential productivity gains from the Green Revolution between conception and age 1 leads to a higher risk of diabetes compared to exposure after age 1. Specifically, I observe a slight increase in diabetes among cohorts born between 1966 and 1968, no effect for those born between 1969 and 1970, and a consistent rise in incidence estimates for cohorts born after 1970.

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

Appendix Figure A.15 shows the event-study estimates for the effect on neurological issues. The pre-Green Revolution trends for treatment and control cohorts are nearly identical, supporting the assumption that, in the absence of the Green Revolution, outcomes would have evolved similarly. I find no increase in neurological issues for cohorts born between 1966 and 1971; however, there is a rise in incidence for those born after 1971. This suggests that exposure to potential productivity gains from the Green Revolution between conception and age 1 is linked to a higher incidence of neurological issues, particularly for cohorts born after 1970.

5.4 Identification Threats

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

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

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

Appendix Tables A.42 to A.45 present the results of the effects of potential productivity gains on height, the metabolic syndrome index, cognitive imbalance index, and motor deficit index, while allowing for linear time trends depending on the baseline urban population share, literacy rates, and employment in the service sector. The effect on height remains stable and statistically significant at the 10% level. Estimates for the metabolic syndrome index are positive but not statistically significant. Among its components, the estimate for hypertension is both positive and significant at the 5% level. Additionally, the estimates for the cognitive imbalance index and motor deficit index are positive but statistically insignificant.

Appendix Tables A.46 to A.49 present the results of the effects of potential productivity gains on height, metabolic syndrome index, cognitive imbalance index, and motor deficit index while allowing for linear time trends depending on the share of health care centers. Due to the availability of baseline data on the share of healthcare centers for only 140 districts, the number of observations decreases. Nevertheless, the results remain consistent with previous findings. The effect on height is negative and statistically significant at the 1% level. Additionally, the estimates for hypertension are positive and significant at the 5% level. I also observe a statistically significant positive effect on the likelihood of receiving a lower score on the cognitive evaluation. For motor deficit, the effect is positive and statistically significant at the 5% level, primarily driven by deficits in grip strength.

Migration Patterns

Being born in a district with high potential productivity gains from the Green Revolution may influence migration patterns across regions. If the Green Revolution affected the likelihood that individuals born after its onset migrated out of their district, my results on health outcomes could be biased. This would result in different exposures later in life compared to individuals born before the Green Revolution. To address this concern, I examine the relationship between potential productivity gains and out-of-district mobility for all individuals in the sample. Appendix Table A.23 presents the results, where the dependent variable is an individual's migration status, defined as whether the individual resides in a district different from their district of birth. The findings suggest that potential productivity gains do not significantly affect migration status. This indicates that the relationship between mobility and exposure to the Green Revolution at birth is unlikely to introduce substantial bias into the analysis.[27]

[27] Furthermore, 99% of individuals in this sample spent at least 15 years of their childhood in the district where they were born, providing further evidence that migration is not contributing to bias in the results.

Spillovers

A key concern in estimating the effects of the Green Revolution on health outcomes is the potential for spillovers across districts, which could lead to violations of the Stable Unit Treatment Value Assumption (SUTVA). SUTVA assumes that the treatment in one unit does not affect outcomes in other units. In this context, it may be violated if agricultural production changes or variations in nutritional availability in one district influence health outcomes in neighboring districts. For example, in the case of highly efficient markets, surplus food from districts with high productivity gains due to the Green Revolution could flow into districts with lower or no gains. This introduces two possibilities for the control group. First, if these neighboring districts gain access to crops that were previously unavailable, it could lead to dietary diversification and better calorie intake, resulting in improved health outcomes like height. This would lead to a scenario where the control group sees significant improvements. In this case, the apparent negative effect observed in my analysis could actually be due to the large positive changes in the control group, overstating the negative impact of the Green Revolution. Second, if the surplus food simply makes the diet more calorie-dense but doesn't improve its diversity, the control group could see a decline in diet quality, leading to a worsened health outcome (such as height). In this case, the total effect would be attenuated, meaning my estimates might be underestimated, and the negative effects of Green Revolution exposure could be more pronounced. The first scenario, with spillover benefits in control districts, raises concern about the accuracy of my results.

I address the concern in the first scenario in three ways. First, as noted in Section 2.2, historical evidence indicates that markets in India were characterized by inefficiency and limited integration, with local consumption closely linked to local agricultural production. Notably, contemporary research by Kapur and Chatterjee (2016) reveals significant spatial price dispersion for agricultural commodities between 2005 and 2014, highlighting that these price differentials persist well into recent decades, long after the Green Revolution and the economic liberalization of the 1990s. Utilizing high-frequency price data for various food crops, they demonstrate that price variability among agricultural markets, or mandis, has remained high across different crops during this period. Furthermore, their analysis underscores considerable within-state variation, further illustrating the constraints of market integration. This suggests that the potential for spillovers between regions, and their likelihood to significantly affect health outcomes in the control group, appears minimal during the 1945–1985 time period.

Despite the evidence indicating inefficiencies and limited integration in Indian agricultural markets, there remains a possibility that spillovers or market dynamics could still affect the control districts. In this context, Andrle and Blagrave (2020) find a significant relationship between cross-market price integration and both the quality of infrastructure and geographical proximity. Based on this, next, I calculate the average road length of neighboring districts at the baseline. This is done by summing the total road length (in kilometers) of districts within a specified cutoff distance and dividing by the number of neighboring districts within that distance. I then interact this measure with a linear time trend to control for potential spillover effects that could bias the health outcome estimates.[28] The results presented in Appendix Tables A.3 to A.6 show that the effect of potential productivity gains on health outcomes remains consistent with previous findings, suggesting that spillovers are less likely

[28] I use various cutoff distances for neighboring districts—specifically 100, 200, 300, 400, and 500 kilometers

to bias the results. Finally, I calculate the average kilometers of railway lines in neighboring districts at the baseline, similarly to the method used for road length, and interact it with linear time trends to control for potential spillover effects. The results, presented in Appendix Tables A.7 to A.10, align with the prior findings.[29]

Envisioning further threats to the identification strategy is challenging, as these would need to explain the differences in health outcomes between districts with varying potential productivity gains for those born just after 1966 while having no effect on individuals born before that time. Nonetheless, I perform a stringent analysis by including district-specific trends. Appendix Tables A.38- A.41 present the findings after controlling for these district trends. The negative effect on height remains consistent in magnitude but loses statistical significance following the inclusion of district trends. This change in significance partly reflects a reduction in statistical power due to this additional control. However, the coefficient for the metabolic syndrome index changes signs after incorporating district trends, suggesting sensitivity to these trends. This sign reversal may indicate that district trends are capturing much of the variation in the independent variable. Results for cognitive imbalance and motor deficit remain positive but are statistically insignificant.

5.5 Treatment Effect Heterogeneity

I explore treatment effect heterogeneity in three ways: gender, family background, and religion.

Gender

First, I explore heterogeneity by gender by interacting the key treatment variable with an indicator for whether an individual is female. Table A.11 shows that while the negative relationship is statistically significant for both males and females, the estimates are higher for males. One potential explanation for the height differences between males and females lies in medical literature. Studies in both animals and humans indicate that male fetuses are more vulnerable to prenatal adversities due to their higher growth demands (Dearden et al., 2018; Alur, 2019). This vulnerability could explain the stronger negative effects of nutritional inadequacy on height observed in males. Additionally, Table A.12 shows little to no treatment effect heterogeneity across genders for the metabolic syndrome index. Appendix Table A.14 also shows a stronger effect for males.

Family Background

Next, I examine the heterogeneity of effects based on the family background. Appendix Tables A.15-A.18 present results by interacting the key treatment variable with an indicator for whether an individual grew up in a lower-income family during childhood. I find no evidence of treatment effect heterogeneity for height. However, for the metabolic syndrome index and motor deficit index, the effects are stronger and more pronounced for individuals from lower-income families. This indicates that

[29] I calculate the average kilometers of railway lines in the neighboring districts at the baseline from Fenske et al. (2023) for the year 1931. Railway expansion between 1931 and 1945 slowed down, as resources were redirected to the war effort during World War II (Bogart and Chaudhary, 2015), (see here).

individuals born after the Green Revolution in districts with higher potential productivity gains, and from lower-income families, are more likely to exhibit higher incidences of diabetes, hypertension, and motor deficits.

Religion

Next, I examine the heterogeneity of effects based on religion, as dietary practices differ between Hindus, who are more likely to follow entirely plant-based diets, than non-Hindus. Changes in nutritional availability from plant-based sources may therefore disproportionately impact Hindus. Appendix Tables A.19-A.22 present the results by interacting the key treatment variable with an indicator for whether an individual belongs to the Hindu religion. I find no evidence of significant treatment effect heterogeneity. While the interaction coefficients suggest a greater decline in height and a higher incidence of metabolic syndrome among Hindus, these results are not statistically significant.

6. Consumption Channel and Alternative Mechanisms

Having established the decline in nutrient availability and its connection to adverse health outcomes, I now turn to examine how these effects are linked to consumption patterns. I then explore alternative mechanisms that may help explain the observed health outcomes.

6.1 Dietary Factors

Changes in household diets around the time of birth, as discussed in Sections 2.2 and 2.3, may account for adverse health outcomes for individuals born after the Green Revolution. This is likely due to altered nutrition during pregnancy, such as a maternal diet low in protein, iron, folate, and other nutrients, or in early infancy, both of which could have long-term effects on health outcomes.

As mentioned in Section 2.2, consumption patterns in India might be localized due to lower market integration and trade restrictions. These constraints might limit the ability of households to access diverse food sources, thus intensifying the impact of local crop production on diets. To understand the link between consumption and production, I examine the cross-sectional relationship between district-level crop production and consumption patterns. To assess this relationship, I calculate the per capita consumption of each crop at the household level using 30-day recall data from the National Sample Survey: Consumption Expenditure data (1999-2000) described in Section 3.4. First, I divide the total household consumption of a particular crop by the household size. After obtaining per capita consumption for each household, I then take the average value of per capita consumption across all households within a district to derive the district-level average per capita consumption. This district-level average is used in the analysis to compare it with the district-level per capita crop production. The relationship is captured using the following model:

$$Consp_{i,d,s} = \alpha + \beta Prod_{i,d,s} + \delta_s + \varepsilon_{i,d,s} \tag{5}$$

where $Consp_{i,d,s}$ is the consumption per capita of crop i in district d and state s. $Prod_{i,d,s}$ is the production per capita of crop i in district d and state s. δ_s are state fixed effects. The crops used in this analysis are rice, wheat, pearl millet, finger millet, maize, barley, sorghum, chickpea, and pigeon pea. The results presented in Table 9, show a strong positive correlation between district-level crop production and consumption patterns, indicating that local production patterns are closely linked to consumption habits.

Shifts in crop production and nutritional availability during early childhood may influence adult dietary preferences. The increased availability and relative price decline of rice and wheat could contribute to these changes, especially given the cultural perception of these grains as superior foods. As a result, there may be a gradual shift away from millets, which are often viewed as inferior. This dietary shift may reflect aspirations for social mobility, where a focus on superior crops signifies upward progress. Additionally, the labor-intensive processing of millet compared to the easier preparation of rice and wheat may further drive these changing preferences. The absolute decline in the availability of pulses and their rising prices could also contribute to a greater reliance on cereals like rice and wheat.

To effectively measure changing dietary preferences among pregnant women and infants, individual-level data is essential. However, the scarcity of individual-level dietary data from the 1960s limits my analysis of how the diets of pregnant women and infants evolved during that period. Nonetheless, I provide suggestive evidence that dietary factors may be driving the observed health outcomes. Firstly, I compare the shares of household expenditure across various categories—cereals, pulses, edible oils, fruits and vegetables, milk and sugar and eggs, meat, poultry, and fish—between men born before and after the Green Revolution across districts with varying levels of potential productivity gains. There are two caveats of this analysis. First, the consumption expenditure data from LASI is collected at the household level, limiting individual-level insights. Following Sekhri and Shastry (2024), I focus on men, as they are likely to have higher consumption within the household. Second, the data on cereal expenditure aggregates rice, wheat, and millet without distinguishing between these individual crops. Similarly, the expenditure data on milk and sugar doesn't distinguish between them. The results are presented in Appendix Table A.54. While the estimates indicate a positive relationship for the share of cereal expenditure and a negative association for the share of pulse expenditure, these findings are statistically insignificant. One possible explanation for the insignificant differences is that individuals born just before the Green Revolution may also experience changes in their dietary preferences over time due to increased exposure to wheat and rice.

Secondly, using the same design as in equation (3), I investigate treatment effect heterogeneity based on the share of household expenditures on different categories. Specifically, I categorize the shares of cereal, pulse, and egg and meat expenditures as low or high by creating indicator variables, where 'high' is defined as having a share greater than the sample mean. As mentioned above, a caveat in the data is that the cereal expenditure aggregates rice, wheat, and millet without distinguishing between these individual crops. Therefore, a high share of cereal expenditure might suggest greater millet consumption; however, this is unlikely due to the overall decline in millet consumption in India during the analysis period. Instead, it is more probable that this expenditure reflects increased consumption of refined grains, such as rice and wheat, along with their products, which have been linked to adverse cardiovascular health outcomes (Swaminathan et al., 2021). However, the results of this analysis should be interpreted with caution, as the inability to differentiate between individual cereals limits the validity of the findings. Appendix Table A.55 shows that the incidence of hypertension and diabetes are more pronounced for individuals living in households with a high share of cereal expenditure. The estimates for treatment heterogeneity based on the share of pulse expenditure are statistically insignificant across all outcomes (Appendix table A.56). However, the treatment heterogeneity coefficient related to a high share of egg, poultry, fish, and meat expenditure is negative, suggesting that individuals from households with a greater share of these expenditures have a lower incidence of diabetes compared to those from households with a lower share (Appendix table A.57).

In the next part of my analysis, I focus on households utilizing ration cards to acquire staples such as wheat, rice, and millet, as the LASI only provides household consumption (in kilograms) data for these three crops when purchased from ration shops. I investigate whether adult males born after the Green Revolution reside in households that have higher per capita consumption of rice or wheat compared to those born before the Green Revolution and whether this difference is more pronounced in districts with higher potential productivity gains. Appendix Table A.58 shows that men born after the Green Revolution in districts with higher potential productivity gains reside in households that consume more rice per capita. The estimates for wheat and millet are statistically insignificant. Using the same treatment heterogeneity framework as above, I also analyze health outcomes for individuals living in households that use ration cards. The findings reveal qualitatively similar results.

I provide additional pieces of suggestive evidence from household-level food consumption data from the National Sample Survey: Household Consumption Expenditure (1999-2000). I examine whether individuals born after the Green Revolution in districts with higher potential productivity gains live in households with worse nutritional adequacy relative to recommended levels, compared to those born before this period. Similar to LASI, the consumption expenditure data from the NSS is collected at the household level, which limits the ability to draw individual-level insights. As a result, I follow the approach from Sekhri and Shastry (2024) and focus on the birth year of men, as they are likely to account for a larger share of household consumption compared to women and children. My analysis examines the nutritional adequacy ratio for calories, carbohydrates, protein, iron, zinc, folate, vitamin B1, vitamin B2, and calcium. Additionally, it is important to note that for this dataset, I match potential productivity gains at the district level with the district of residence rather than the district of birth, as the dataset does not provide information on the district of birth.

Appendix Table A.59 presents the findings for caloric and macronutrient adequacy (carbohydrates and protein). I find no evidence of individuals born after the Green Revolution residing in households with lower caloric or macronutrient adequacy compared to those born before, particularly in districts with higher potential productivity gains. Appendix Table A.60 shows the results for the standardized micronutrient adequacy index and the components: iron, zinc, folate, vitamin B1, vitamin B2, and calcium. Although the estimates are negative, the coefficients are not statistically significant.

Further, I conduct a heterogeneity analysis examining individuals residing in rural and urban households, with the results presented in Appendix Tables A.61–A.62. For calorie and macronutrient deficiency, I do not observe any significant effects for individuals residing in either rural or urban households. However, when focusing on micronutrient adequacy, I find that men born after the Green Revolution in rural areas with higher potential productivity gains are more likely to live in households with lower adequacy of iron, zinc, folate, vitamin B1, vitamin B2, and calcium. These estimates are not significant for households in urban areas.

6.2 Alternative Mechanisms

Other in-utero exposure

The Green Revolution might have influenced height and other health outcomes through higher pesticide exposure which is unrelated to nutrition. For instance, shifts towards HYV wheat and rice because of higher potential productivity gains can lead to increased exposure to chemical pesticides and fertilizers. Exposure to agrochemicals, such as pesticides and fertilizers, can have detrimental effects on health, particularly during critical developmental periods. Studies have shown that early-life exposure to these chemicals may impair growth, leading to reduced height. Agrochemical exposure has also been linked to an increased risk of metabolic disorders, such as diabetes and hypertension, by disrupting endocrine functions. Additionally, the neurotoxic effects of certain pesticides can negatively affect cognitive development, resulting in long-term cognitive deficits (Eskenazi et al., 2004; Jaacks et al., 2024; Calzada et al., 2023). I present evidence suggesting that agrochemicals are unlikely to be the main drivers of these results in three key ways. First, my preferred models control for fertilizer exposure at the birth year and birth-district levels, and the results remain statistically significant after accounting for this factor. Second, drawing on the approach from Brainerd and Menon (2014), I examine whether individuals born during the peak months of fertilizer and pesticide application for wheat and rice sowing exhibit different health outcomes, as they would have been exposed to higher levels of agrochemicals. The results, presented in Appendix Tables A.24 to A.27, show no evidence of treatment effect heterogeneity based on birth during the sowing months. Third, I test whether individuals born in rural areas, where agrochemical exposure is more common, experience worse health outcomes compared to those born in urban areas. However, one concern here is that dietary changes may also be pronounced in rural areas, which can make the result difficult to interpret. Nevertheless, I explore this possibility by interacting the key treatment variable with an indicator for rural birth. The results, presented in Appendix Tables A.50 to A.53, show smaller negative effects on height for rural-born individuals. Additionally, there is little to no impact on metabolic syndrome, cognitive imbalance, and motor deficit indices, with some indications of lower incidence for rural-born individuals. The results suggest that agrochemical exposure is unlikely to be the main factor behind the observed health outcomes. One explanation for the smaller effects in rural areas is that improvements in caloric sufficiency may partially offset declines in nutritional quality, especially if rural areas had lower baseline caloric intake compared to urban areas.

Adult Health Behavior

To further understand mechanisms, I also explored how the effect of the Green Revolution exposure on health outcomes changes if I control for adult health behaviors such as smoking, alcohol consumption, and exercise.[30] The estimated effects of potential productivity gains on health outcomes as shown in Appendix Tables A.28 to A.31 are little changed when these additional variables are included.

Selection Bias in Health Outcomes

Changes in Population Characteristics: An important concern is that Green Revolution exposure in districts with higher potential productivity gains may alter population composition, potentially changing the characteristics of children born there. Green Revolution exposure could also influence the profile of mothers who give birth, further affecting the health outcomes of children later in life.[31]

Appendix Table A.32 examines whether exposure to the Green Revolution led to a compositional shift in the underlying population. Columns (1)-(3) assess shifts in the share of Scheduled Caste (SC) females, Scheduled Tribe (ST) females, and adult literate females in the total population between the 1961 and 1981 census years. Column (4) examines whether the likelihood of a mother having completed middle school differs for individuals born before and after the Green Revolution in districts with different levels of potential productivity gains. The results provide little evidence for differential sorting along observables that might bias the estimates. The point estimates are not only statistically insignificant but also small in magnitude.

Infant Mortality and Non-Random Selection: Bharadwaj et al. (2020) show that regions in India with higher adoption of HYV crops during the Green Revolution experienced significant reductions in infant mortality. As a result, cohorts born before and after the Green Revolution may differ in health outcomes, not only due to nutritional changes but also because of selection effects—infants who survived due to reduced mortality may have different health endowments, potentially affecting the average health of the cohort. To address this selection bias, I estimate my main regressions on a sample restricted to individuals who would have survived regardless of the Green Revolution's impact. Specifically, I trim the sample by adjusting for the "extra" individuals who survived due to HYV adoption.

Using Bharadwaj et al. (2020), which shows that a 20 percentage point increase in HYV area reduces infant mortality by 0.5 percentage points, I calculate the expected change in infant mortality in districts with higher potential productivity gains. Based on these estimates, my analysis predicts that moving from no HYV adoption to the highest potential productivity gains would lead to a 26.6 percentage point increase in HYV adoption, resulting in a 0.675 percentage point decline in infant mortality. Accordingly, I adjust the population of individuals born after 1966 in districts with higher-than-average productivity gains, focusing on those from low-income families, who are shorter than average for their gender, or who exhibit metabolic syndrome, cognitive issues, or motor deficits.[32] Appendix Tables A.33 to A.36 present the results, where I randomly drop selected observations and include bootstrapped 95% confidence intervals. The results are quite similar to the previous findings, suggesting that the results are not driven by selection effects.

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

[31] Bharadwaj et al. (2020) show that the profiles of mothers giving birth are not different along multiple characteristics.

[32] I trim individuals from the poorest backgrounds with worse health outcomes because they are likely to have had poorer health endowments at birth, which may disproportionately influence the results and skew the analysis of health outcomes in the post-Green Revolution cohorts.

7. Alternative Specifications

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

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

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

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

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

Appendix Tables A.63 to A.66 present the results regarding the impact of the new exposure variable on height, metabolic syndrome index, cognitive imbalance index, and motor deficit index. The findings indicate consistent effects, with magnitudes slightly larger than those observed in previous analyses. Notably, the negative impact on height and the positive effect on the metabolic syndrome index are statistically significant at the 1% level.

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

8. Conclusion

In this paper, I provide new empirical evidence on the long-term health effects of the Green Revolution in India, particularly in relation to the shifts in agricultural production and nutrition. The introduction of HYV crops, while successful in increasing food security and calorie availability, has had unintended consequences for crop diversity and nutritional adequacy. My findings show that districts with greater potential productivity gains from wheat and rice experienced a marked reduction in crop diversity, primarily due to the decline in the cultivation of nutrient-rich crops such as lentils and millets. This shift might have led to a dietary imbalance, with adequate calorie intake but lower levels of essential nutrients like proteins, iron, zinc, and folate.

The health implications of these changes are significant. Cohorts exposed to the Green Revolution during early childhood, particularly in districts with higher potential productivity gains, are shorter and have a higher incidence of metabolic disorders such as hypertension and diabetes. While calorie intake might have improved, the quality of nutrition appears to have deteriorated, contributing to these adverse health outcomes. The findings highlight the importance of considering not just caloric sufficiency but also nutritional quality in agricultural policies aimed at improving food security.

To further investigate the dietary channel, I present suggestive evidence by exploring consumption patterns linked to health outcomes. Individuals born in districts with higher productivity gains after the Green Revolution consume more rice per capita and show a higher incidence of hypertension and diabetes, particularly in households that allocate a greater share of their expenditures to cereals. In contrast, these health conditions are less prevalent among households that prioritize spending on animal-based foods. However, it is important to acknowledge certain limitations: The analysis primarily relies on indirect evidence due to the absence of individual-level dietary data from the study period, which restricts the ability to establish a definitive causal relationship between dietary patterns and health outcomes. I also explore alternative explanations for adverse health outcomes, including agrochemical exposure, urbanization, lifestyle changes, access to health care, and differential survival to adulthood. The evidence does not substantiate these factors as primary drivers of the observed health outcomes. This reinforces the conclusion that dietary shifts likely induced by the Green Revolution play a role in the health challenges identified.

Overall, this research underscores the need for agricultural policies that balance productivity with nutritional diversity to ensure long-term health benefits. As India continues to grapple with the dual burden of undernutrition and rising chronic diseases, lessons from the Green Revolution offers valuable insights for future food and nutrition security strategies. Policymakers must recognize the importance of crop diversity and invest in agricultural practices that promote a more balanced and nutritious diet, particularly in low-income and vulnerable regions.

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Tables and Figures

Figures

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

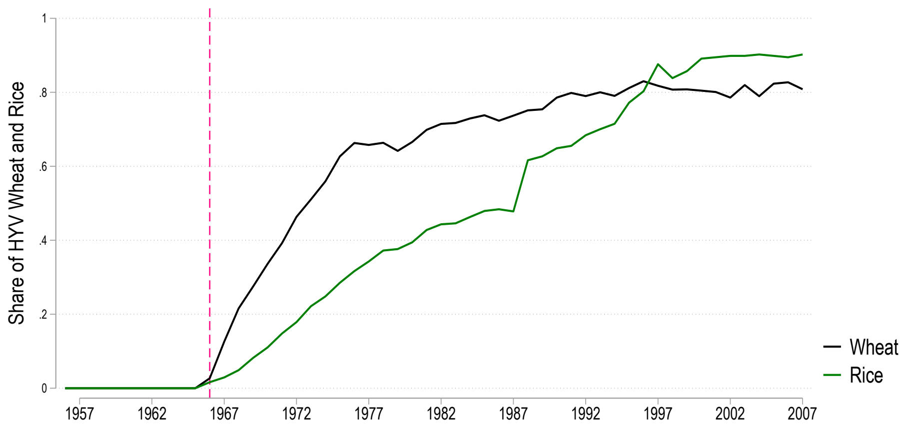
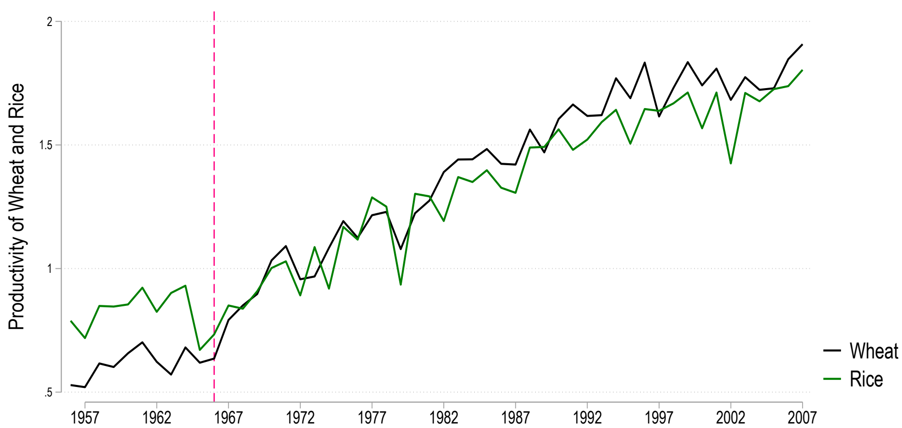
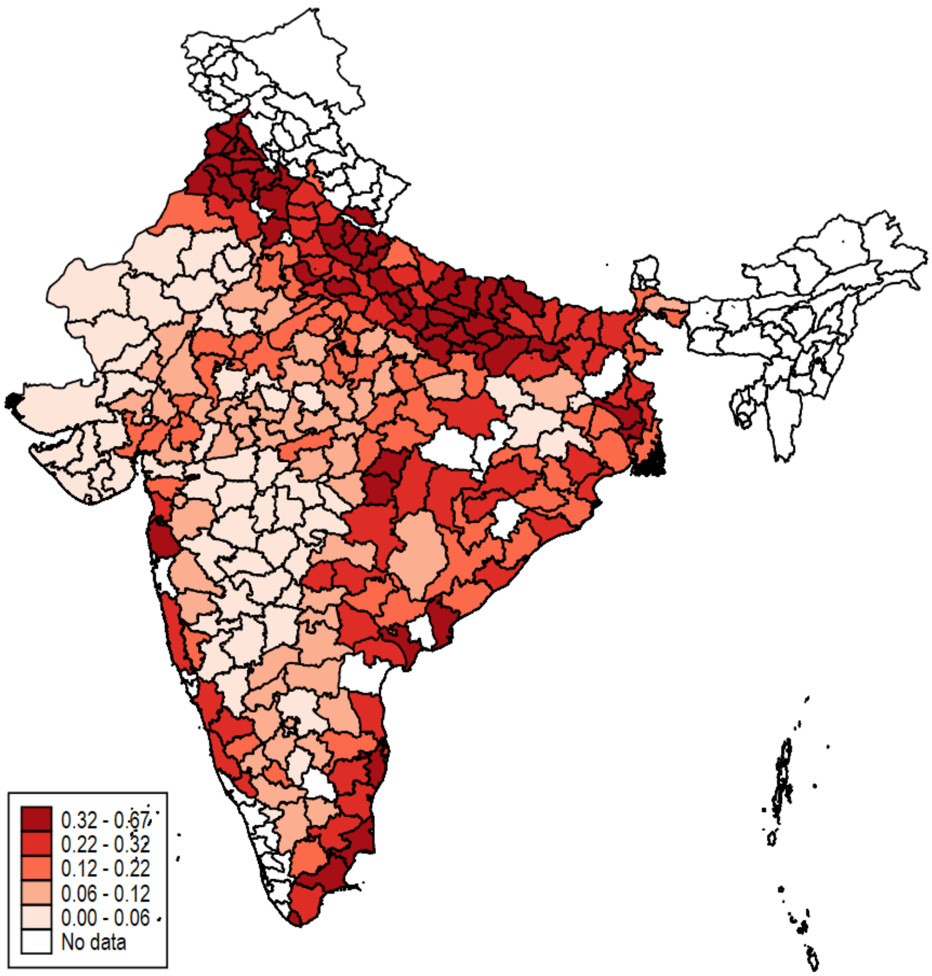


Figure 2: Productivity of wheat and rice (tonnes/hectares)



Notes: Figure 1 shows the fraction of crop land devoted to cultivating the indicated crop in which high yield varieties were used for wheat and rice is on the y-axis. Figure 2 shows the yield of wheat and rice on the y axis. The dotted vertical line is the year (1966) in which the high yield variety for wheat and rice was released in India.

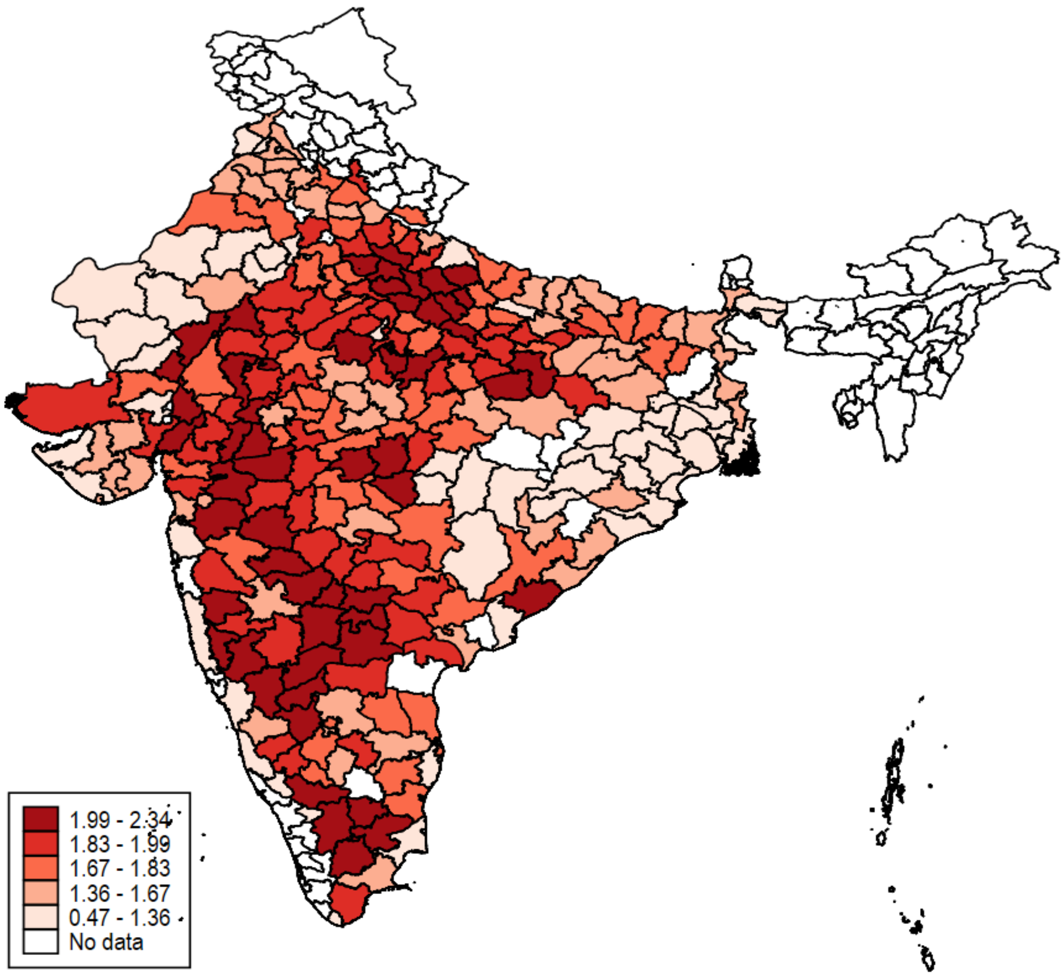


Source: Indian Agriculture and Climate Dataset

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

Notes: This map displays Indian districts in the IACD dataset (267 districts) shaded by share of land under HYV wheat and rice in total cultivated area. Potential productivity gains are calculated as the average of gains for wheat and rice, measured by the difference between potential yields. Unshaded districts were not included in the IACD dataset.

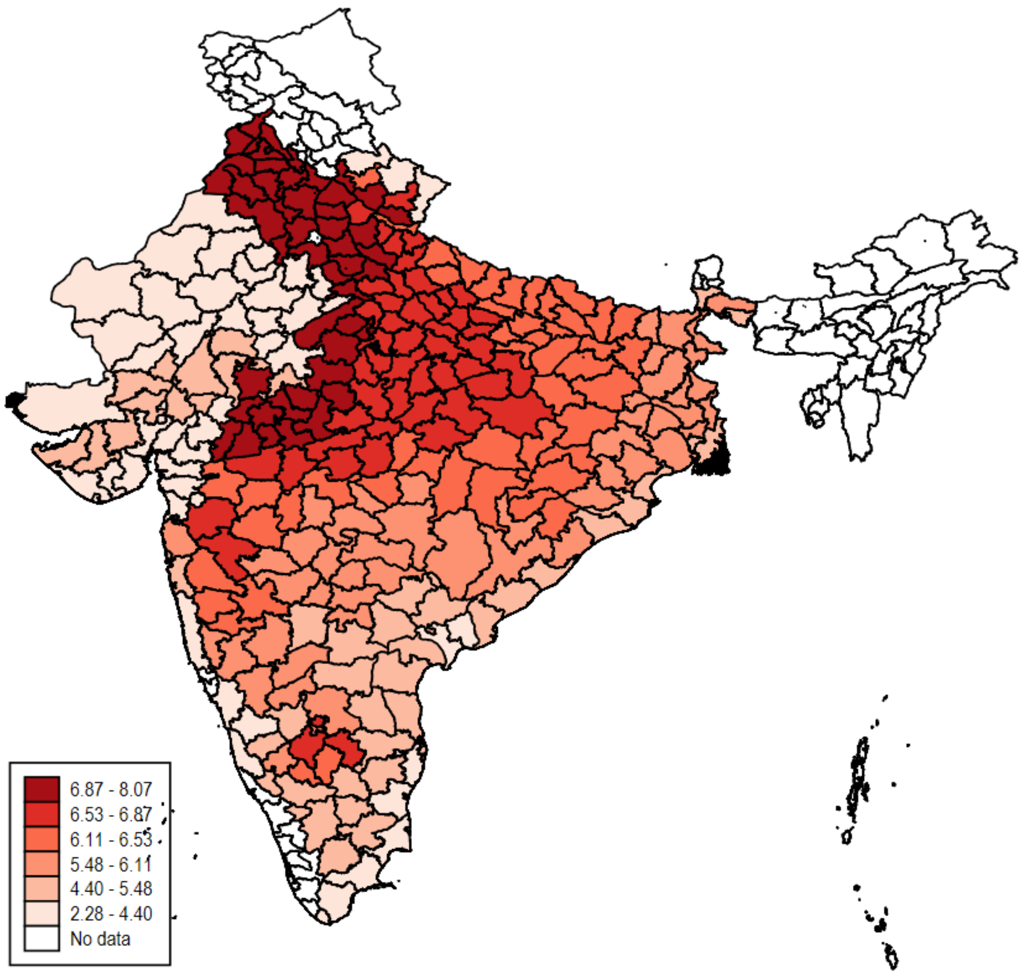
Figure 4: Average crop diversity measured between (1957-2007)



Source: Indian Agriculture and Climate Dataset

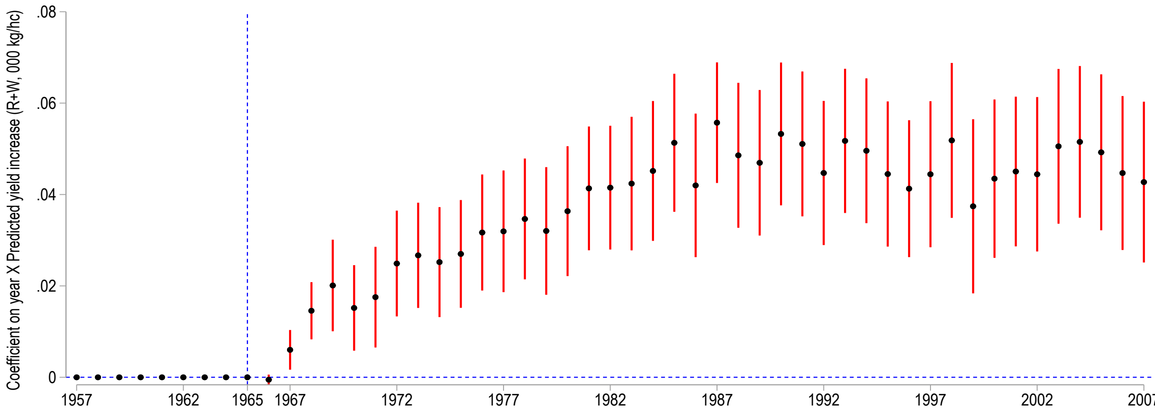
Notes: This map displays Indian districts in the IACD dataset (267 districts) shaded by crop diversity measured using the Shannon Diversity Index. The diversity index is measured as $\sum_{i=1}^{n} p_{i,d,t}\ ln(\frac{1}{p_{i,d,t}})$, where $p_{i,d,t}$ is the area planted under crop i in district d, 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. Unshaded districts were not included in the IACD dataset.

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



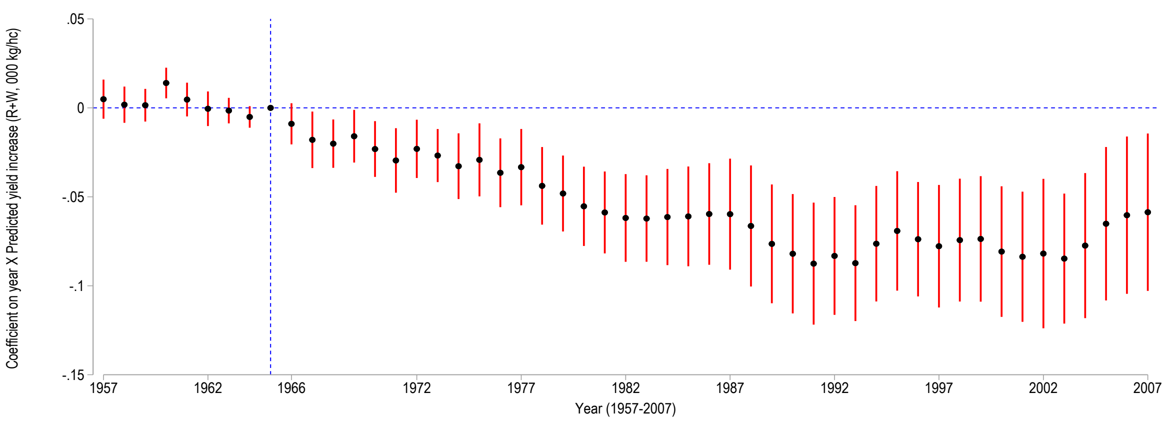
Notes: This map displays Indian districts in the IACD dataset (267 districts) shaded by potential productivity gains (000 kg/hc) calculated using FAO-GAEZ v4.0 dataset. Potential productivity gains are calculated as the average of gains for wheat and rice, measured by the difference between potential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

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



Notes: This figure plots the coefficients from estimating equation 2 using share of area under HYV wheat and rice in total cultivated area as the dependent variable. I use district-level panel dataset (IACD and ICRISAT) from 1957 to 2007. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

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



Notes: This figure plots the coefficients from estimating equation 2 using crop diversity as the dependent variable. Crop diversity is measured using the Shannon Diversity 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 potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

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

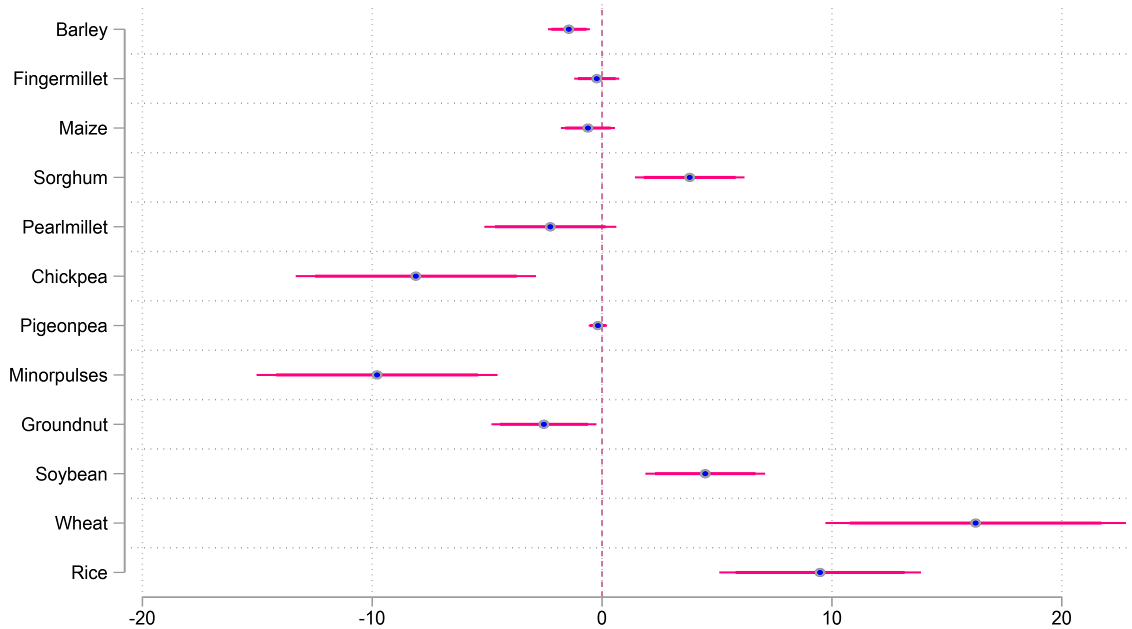
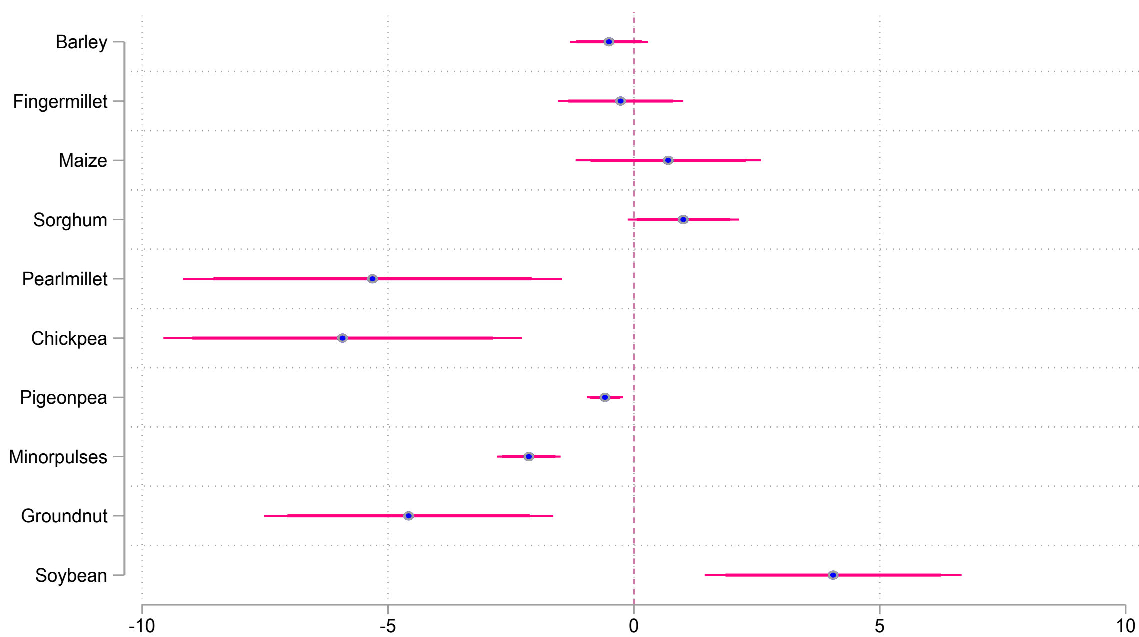
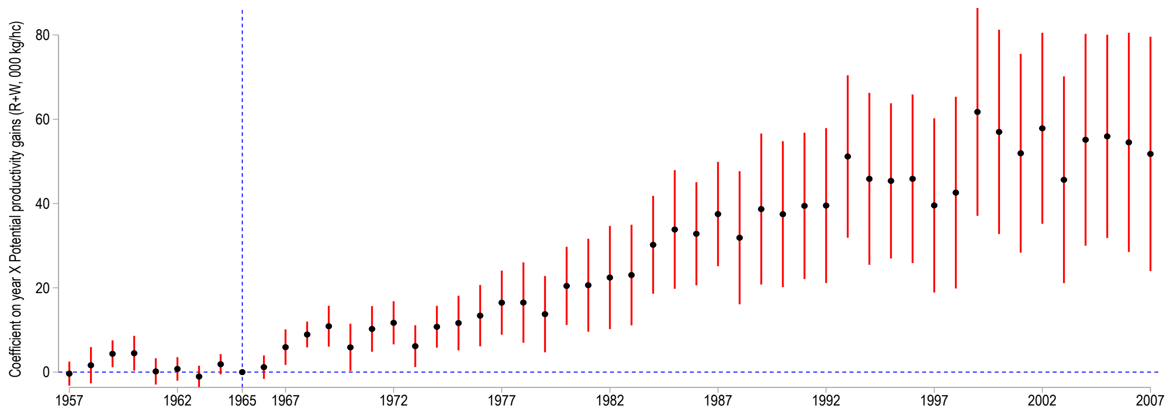


Figure 9: Effect on production (in tonnes) of consumption crops



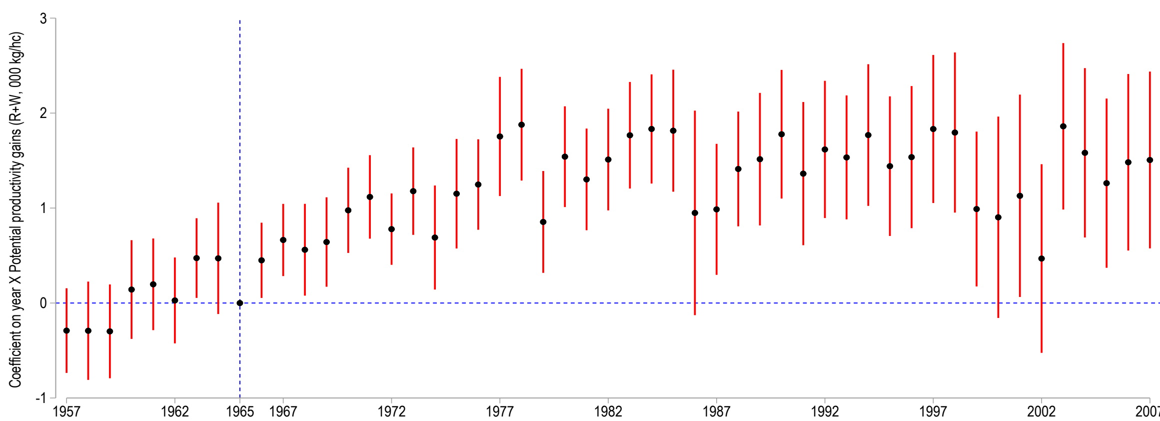
Notes: Figures 8 and 9 plot coefficients and 95% (90%-bolder horizontal lines) confidence intervals from the regression in equation 1 for major consumption crops. The dependent variable in Figure 8 is the area planted under each crop in hectares and in Figure 9 is the production of each crop in tonnes. The explanatory variable is potential productivity gains measured from the FAO-Global Agroeconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The regression also includes geographic controls and district and year fixed effects. Standard errors are clustered at the district level.

Figure 10: Event study estimates of total calorie production



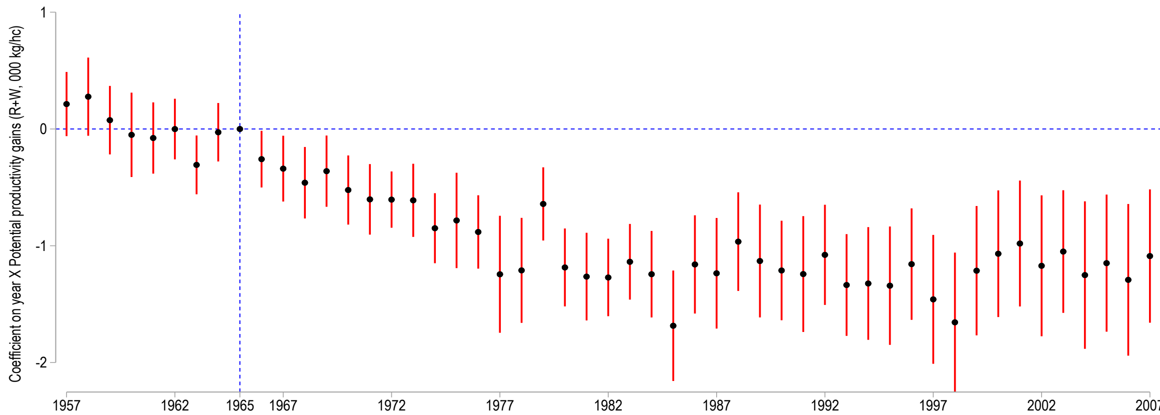
Notes: This figure plots the coefficients from estimating equation 2 using total calorie produced (10^9 kcal) as the dependent variable. The caloric calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The explanatory variable is potential productivity gains measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 11: Event study estimates of carbohydrates per thousand calories produced



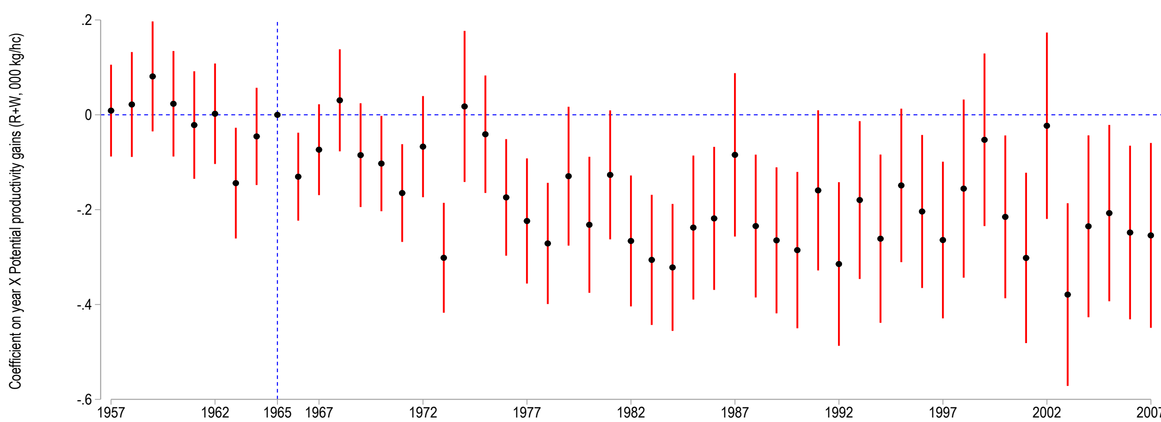
Notes: This figure plots the coefficients from estimating equation 2 using carbohydrate produced per calorie produced (g/000 kcal) as the dependent variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea.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

Figure 12: Event study estimates of protein per thousand calories produced



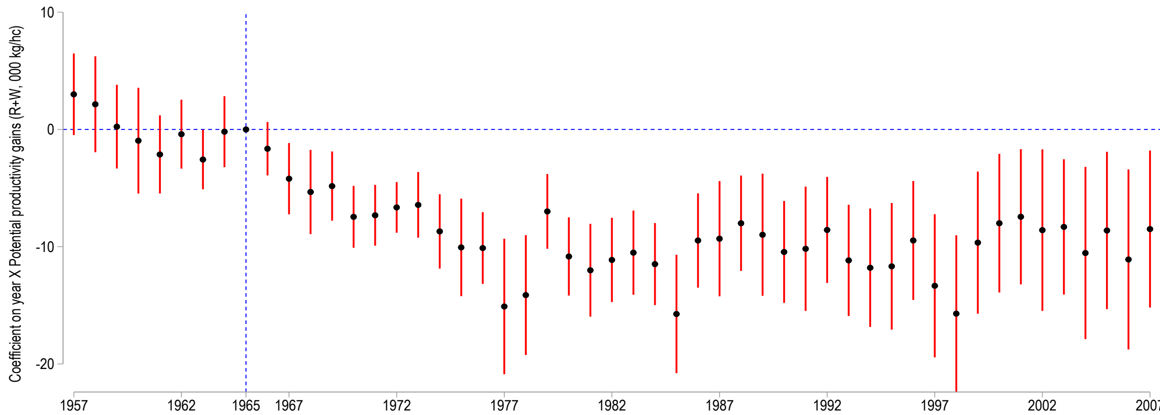
Notes: This figure plots the coefficients from estimating equation 2 using protein produced per calorie produced (g/000 kcal) as the dependent variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea.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

Figure 13: Event study estimates of iron per thousand calories produced



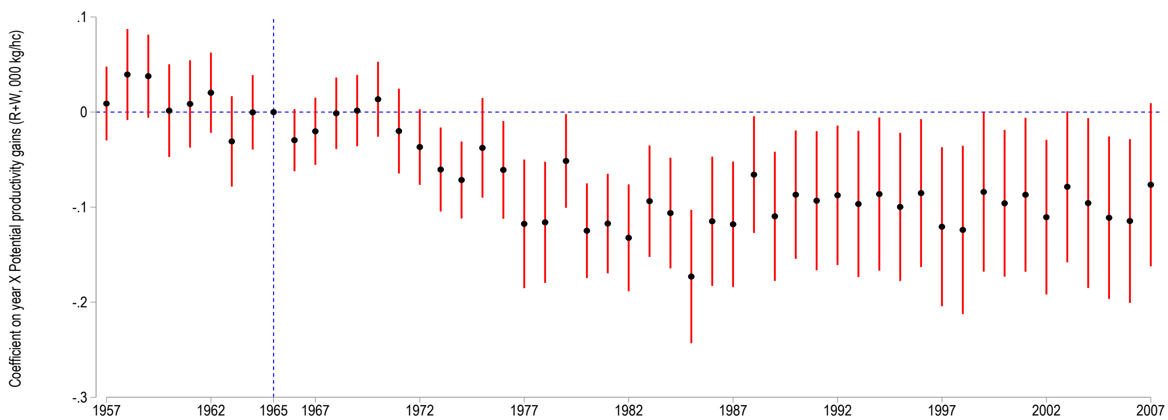
Notes: This figure plots the coefficients from estimating equation 2 using iron produced per calorie produced (mg/000 kcal) as the dependent variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. The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

Figure 14: Event study estimates of folate per thousand calories produced



Notes: This figure plots the coefficients from estimating equation 2 using folate produced per calorie produced (μg/000 kcal) as the dependent 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 Agroeconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The coefficients are plotted for each year from 1957-2007. The reference year is 1965, the year before Green Revolution was implemented in India. The vertical bars represent 95% confidence intervals based on standard errors clustered at the district level.

Figure 15: Event study estimates of zinc per thousand calories produced



Notes: This figure plots the coefficients from estimating equation 2 using zinc produced per calorie produced (mg/000 kcal) as the dependent 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 Agroeconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. 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: Longitudinal Aging Survey of India: Summary Statistics

	N	Mean	s.d.
Individual Demographics			
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 Measures			
Height cms	38071	155.69	8.82
Height Stunting	38071	0.05	0.21
Metabolic Health Outcomes			
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
Cognitive and Motor Health Outcomes			
Neurological Issue=1	41919	0.02	0.14
Grip Strength Deficit	41919	0.40	0.49
Lower Cognitive Score	41919	0.14	0.35
Agrochemical Related Health Outcomes			
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

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

Table 2: Effect of potential productivity gains on HYV adoption

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

Notes: Each column presents the results from estimating equation 1. The dependent variable is the share of area planted using high yielding varieties of wheat and rice in total cultivated area. The sample includes 266 districts in India from 1957 to 2007. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. 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 parentheses and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 3: Effect on crop diversity

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

Notes: Each column presents the results from estimating equation 1. The dependent variable is crop diversity. It is measured using shannon diversity 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) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. 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 parentheses and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

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

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design by estimating equation 1. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. Col (1) is total calories produced measured in (10^9 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 parentheses and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 5: 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.	155.7	155.7

Notes: This table presents the results on the effects of potential productivity gains exposure on height. The unit of observation is an individual born in a specific district and year. The sample, drawn from the 2017 LASI, includes individuals born between 1945 and 1985. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. Standard errors are in the parentheses and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 6: 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}	0.012**	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	0.16	0.8	0.3	0.1	0.03	0.02

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The unit of observation is an individual born in a specific district and year. The sample, drawn from the 2017 LASI, includes individuals born between 1945 and 1985. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. 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 7: 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}	0.005	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	0.02	0.33	0.14

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The unit of observation is an individual born in a specific district and year. The sample, drawn from the 2017 LASI, includes individuals born between 1945 and 1985. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. 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 8: Effect of potential productivity gains on motor skills

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.013	0.007*	-0.001
	(0.010)	(0.004)	(0.003)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.03	0.4	0.2

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice. The unit of observation is an individual born in a specific district and year. The sample, drawn from the 2017 LASI, includes individuals born between 1945 and 1985. The explanatory variable is potential productivity gains (000 kgs/hc) in wheat and rice measured from the FAO-Global Agroceconomic Zones v-4 dataset. The potential productivity gains are calculated as the average of the differences in potential productivity for wheat and rice between low-input, rainfed and high-input, irrigated systems. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. Column 1 shows the effect on motor deficit index. Cols (2)- (3) show the effect on incidence of components of motor deficit. Standard errors are in parentheses and clustered at the district of birth. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table 9: Cross-sectional relationship between production and consumption per capita

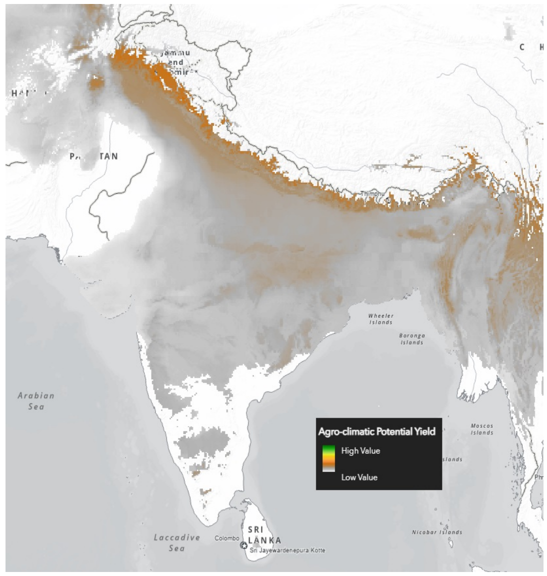
	Consumption per capita (kg/30 days)								
	Wheat	Rice	Maize	FM	Barley	PM	Sorghum	Pigeonpea	Chickpea
Wheat production per capita	0.102***								
	(0.02)								
Rice production per capita		0.166***							
		(0.03)							
Maize production per capita			0.162***						
			(0.03)						
FM production per 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.

A. Appendix

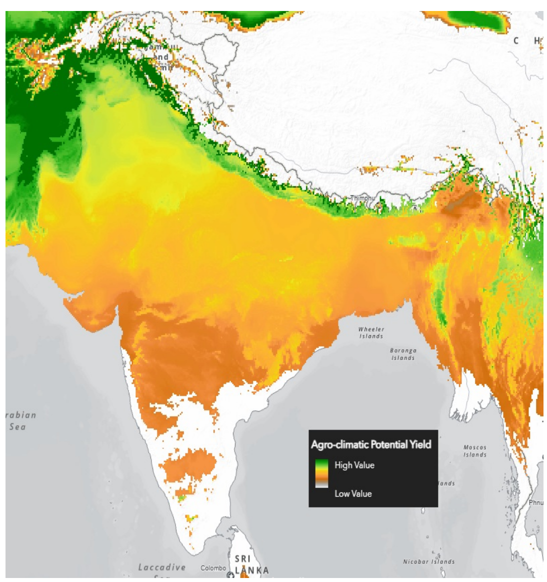
Figures

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

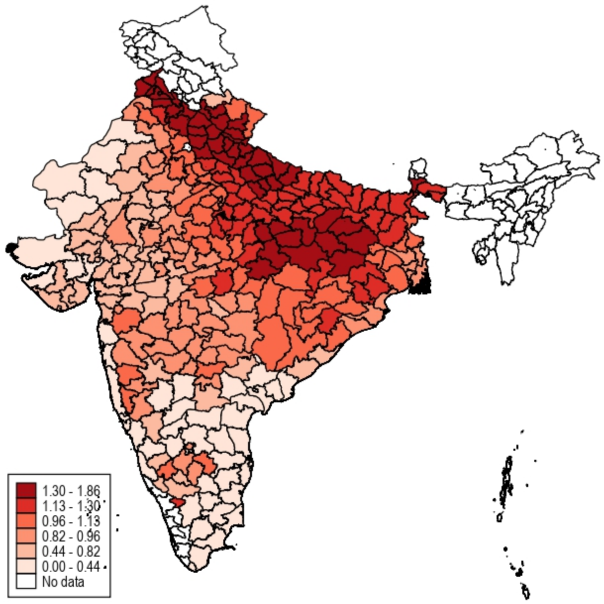


Source: FAO: GAEZ-v4

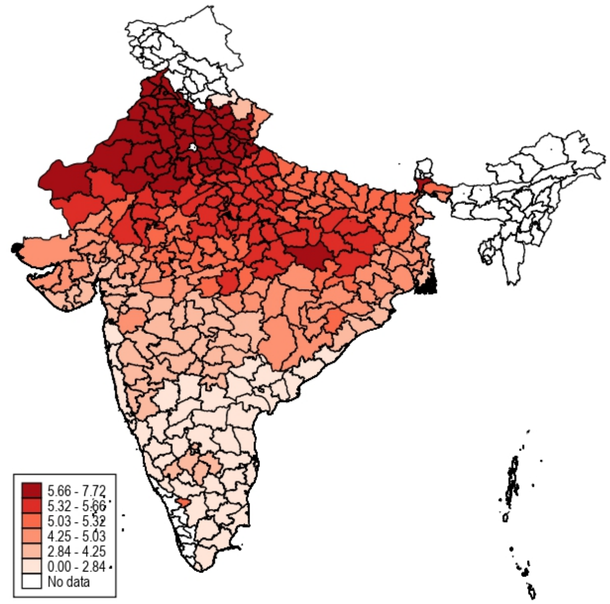
Figure A.2: Potential yield of wheat under high input and irrigated conditions



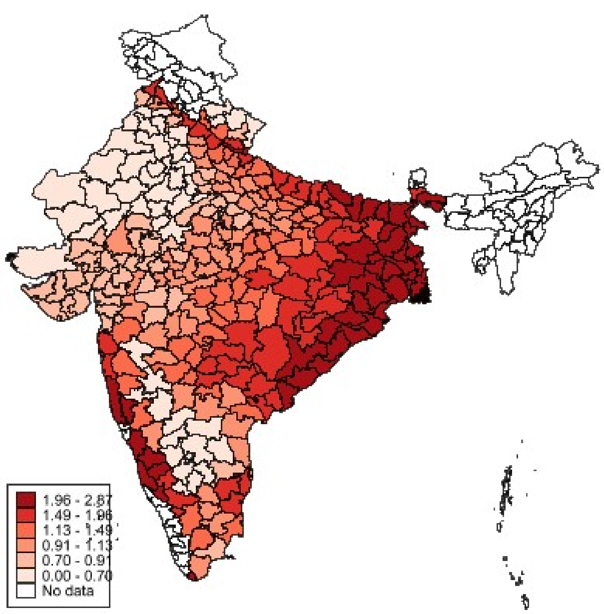
(a) Potential yield of wheat under low input and rainfed conditions: Aggregated Measure



(b) Potential yield of wheat under high input and irrigated conditions: Aggregated Measures



(c) Potential yield of rice under low input and rainfed conditions: Aggregated measures



(d) Potential yield of rice under high input and irrigated conditions: Aggregated measures

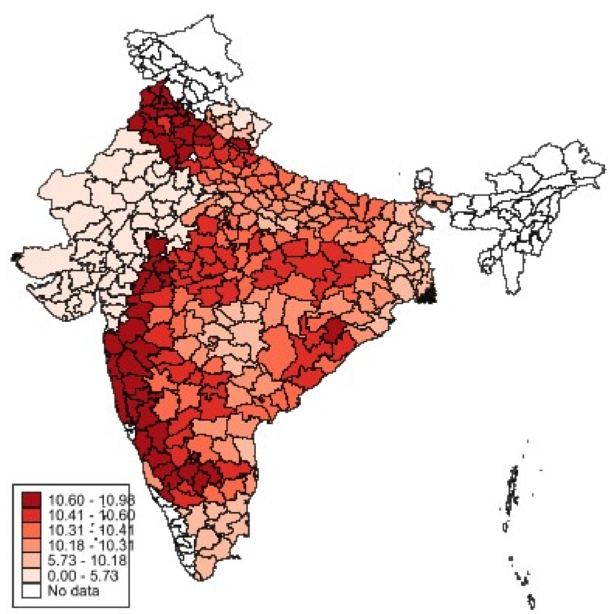
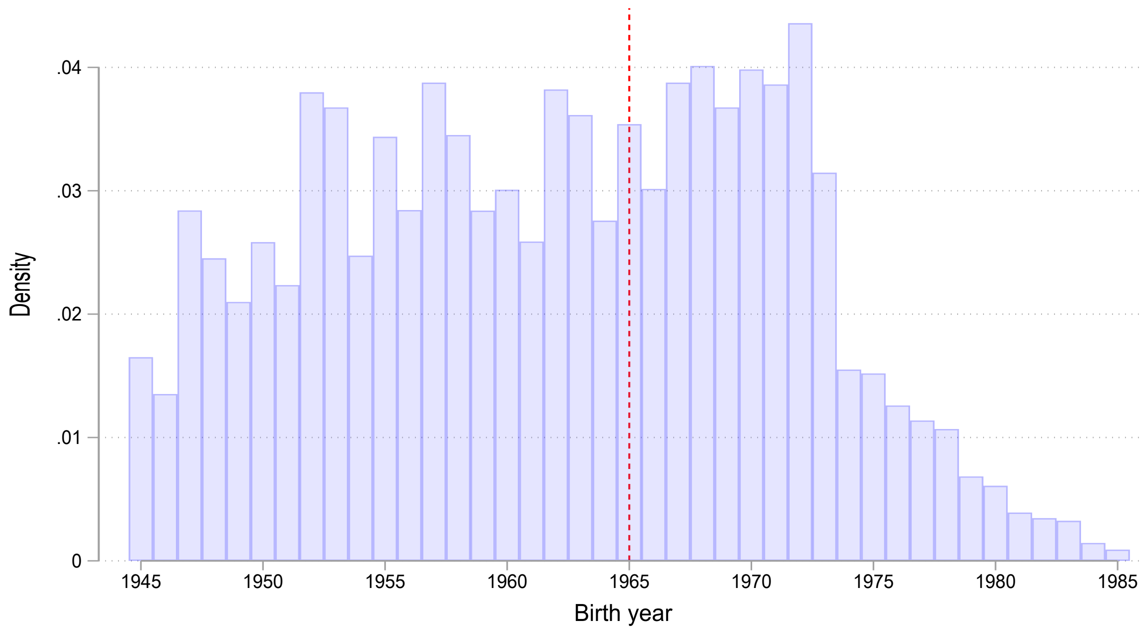


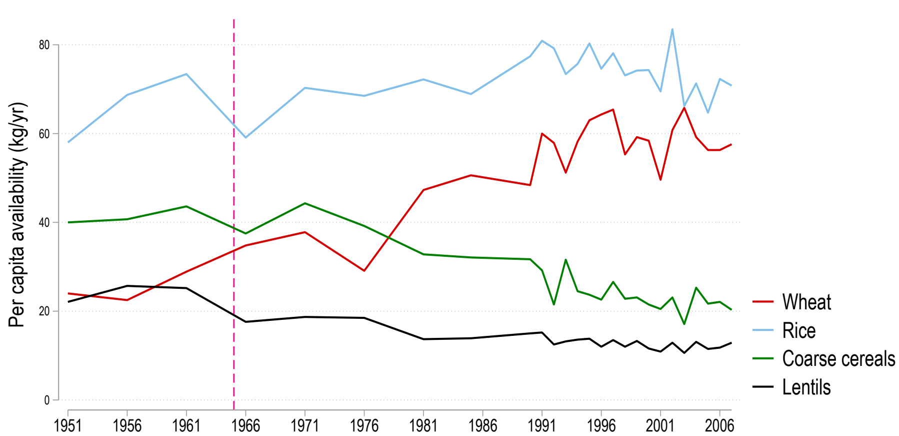
Figure A.3: Potential yield of wheat and rice under different conditions
Source: FAO: GAEZ-v4

Figure A.4: 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.5: Trends in per capita availability of food grains



Notes: Source: ICRISAT Data

Figure A.6: Share of area under wheat in total cultivated area over time

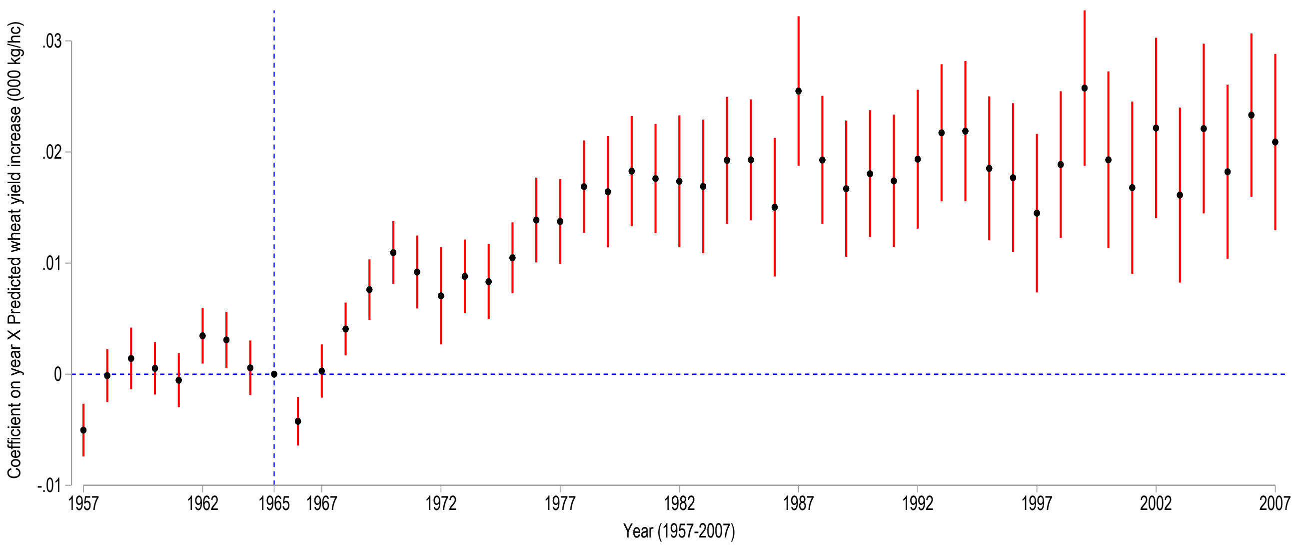
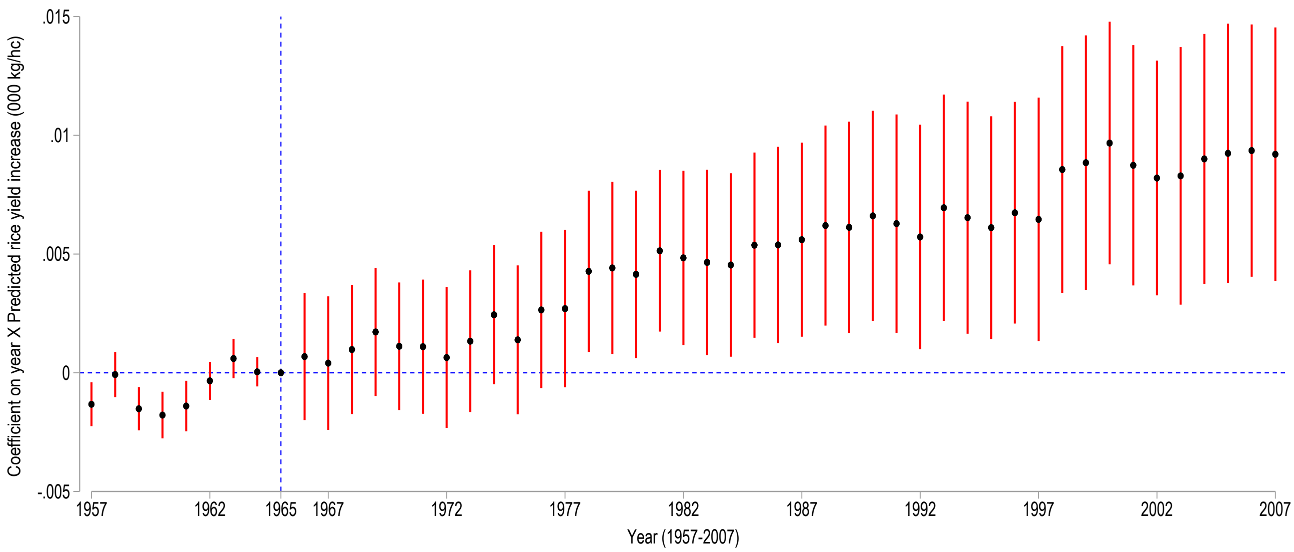
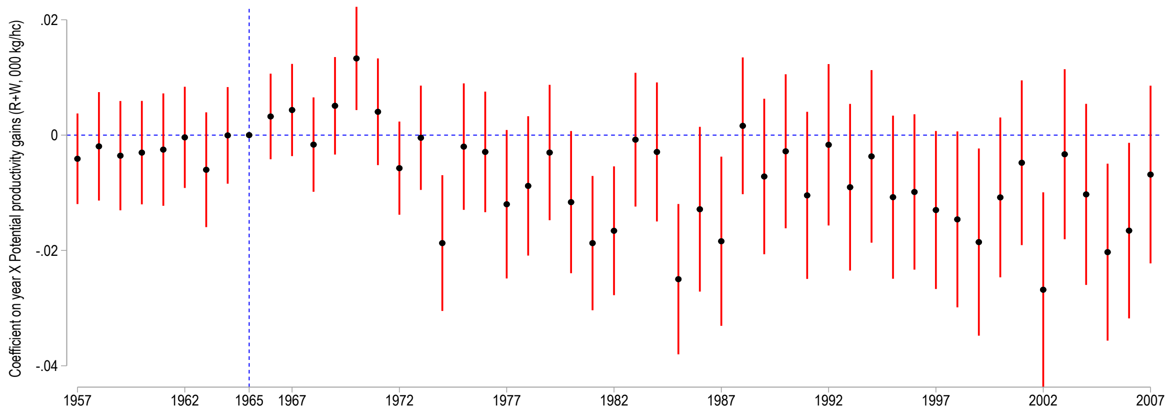


Figure A.7: Share of area under rice in total cultivated area over time



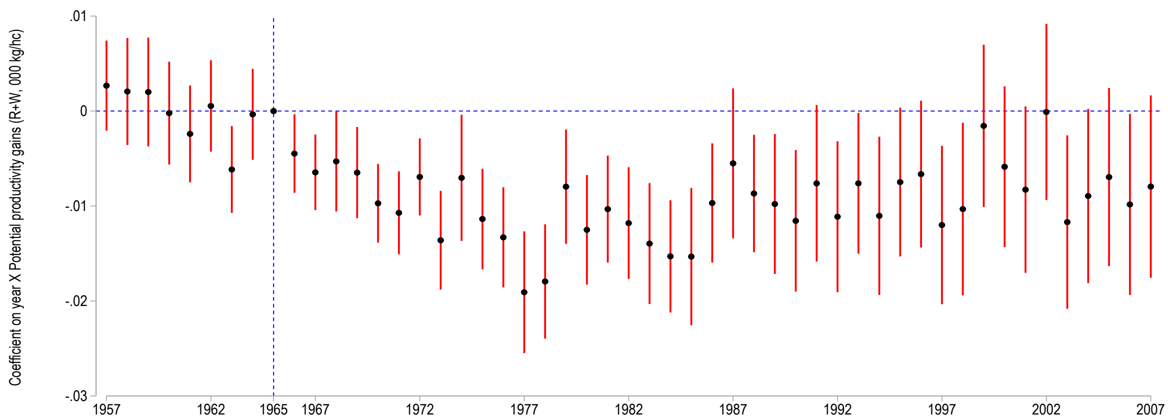
Notes: These figures plot the coefficients from estimating an event-study model using the share of area planted with all high-yield varieties of wheat and rice the dependent variable. The regression includes socio-economic and geographic controls, district and year fixed effects. Vertical bars indicate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

Figure A.8: Event study estimates of vitamin B1 per calorie produced



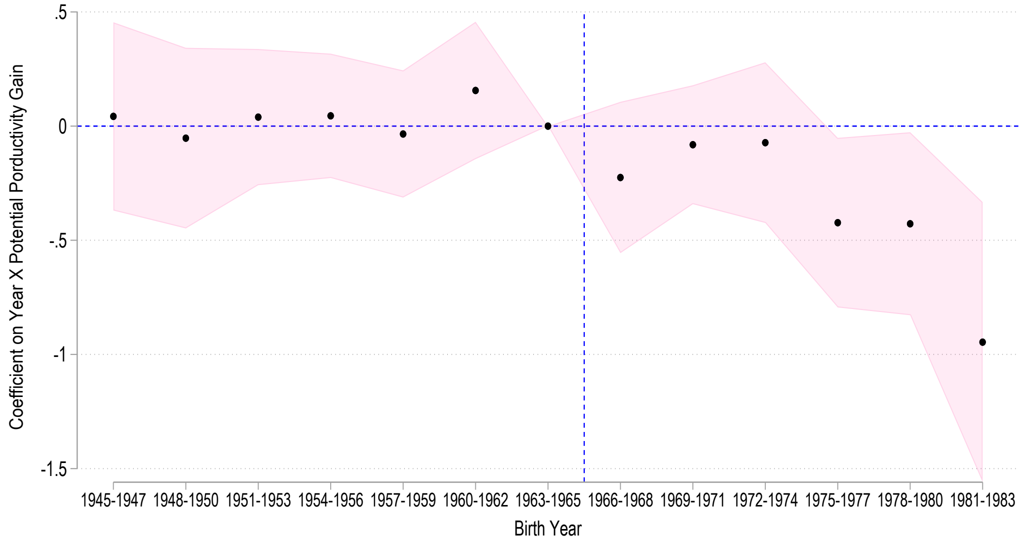
Notes: This figure plots the coefficients from estimating equation 2 using vitamin B1 produced per calorie produced (μg/000 kcal) as the dependent variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. 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 A.9: Event study estimates of vitamin B2 per calorie produced



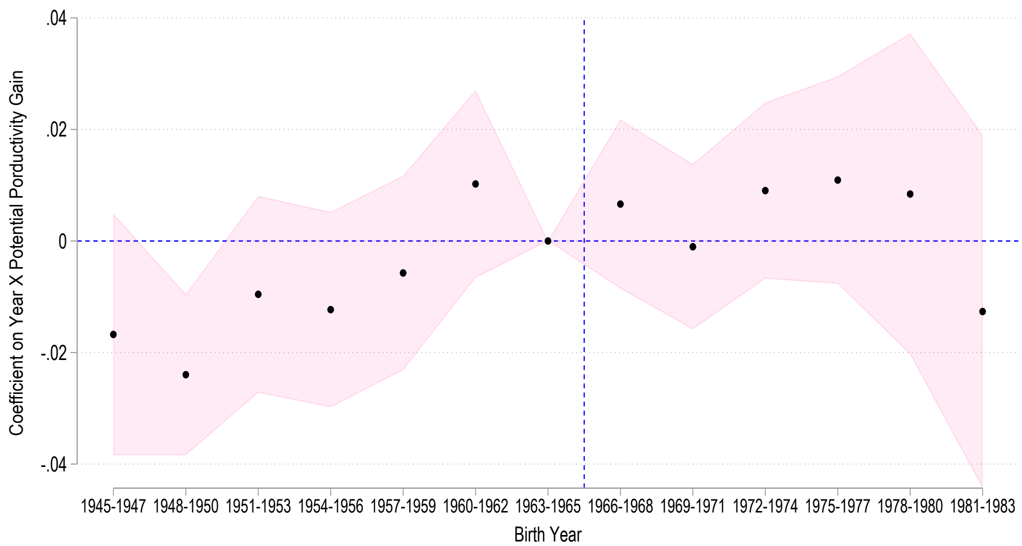
Notes: This figure plots the coefficients from estimating equation 2 using vitamin B2 produced per calorie produced (μg/000 kcal) as the dependent variable. The calculation uses 7 major cereals and 2 major lentils: rice, wheat, sorghum, pearl millet, finger millet, barley, maize, chickpea and pigeonpea. 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 A.10: Event study estimates of the effect of potential productivity gains on height



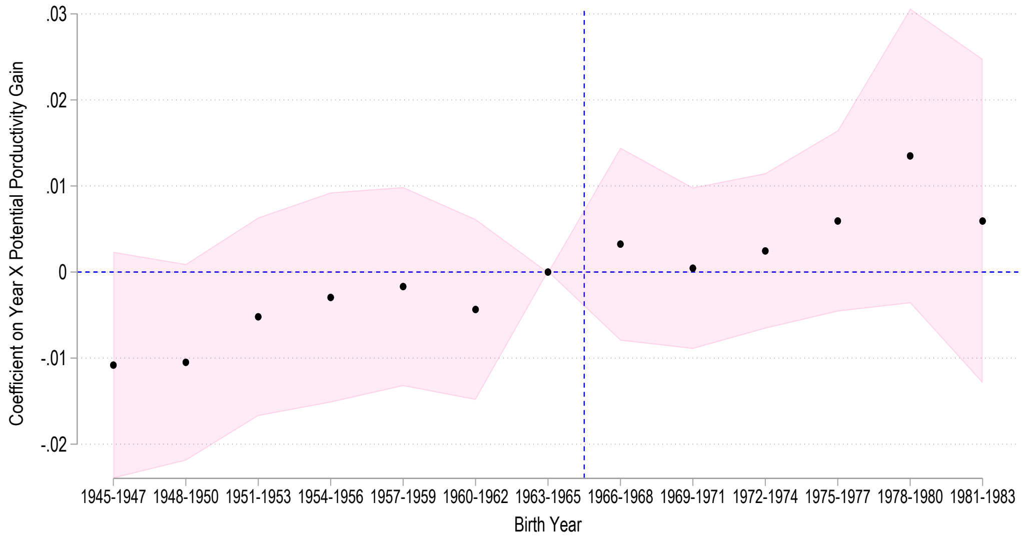
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using height as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: total fertilizer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

Figure A.11: Event study estimates of the effect of potential productivity gains on metabolic syndrome index



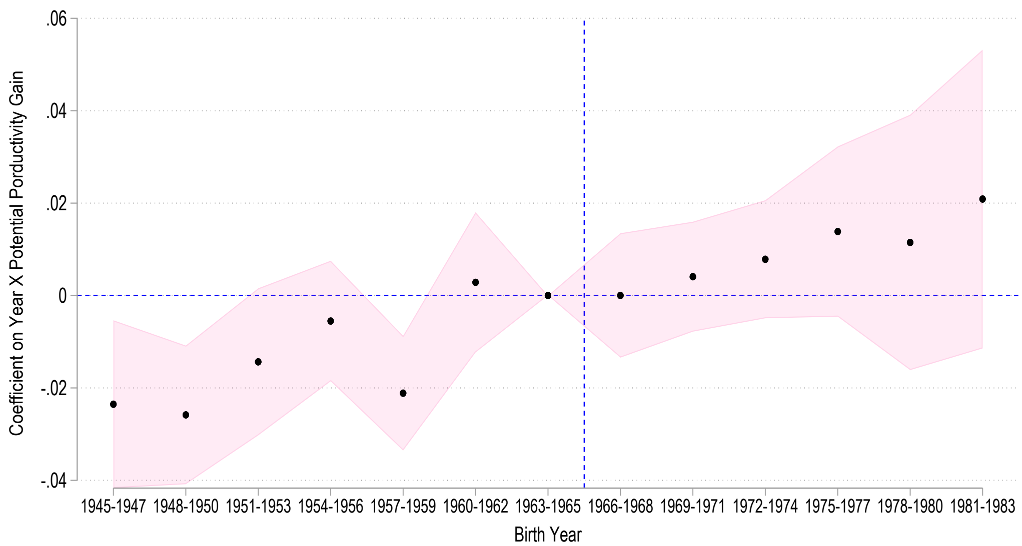
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using metabolic syndrome index as the dependent variable. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: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

Figure A.12: Event study estimates of the effect of potential productivity gains on diabetes



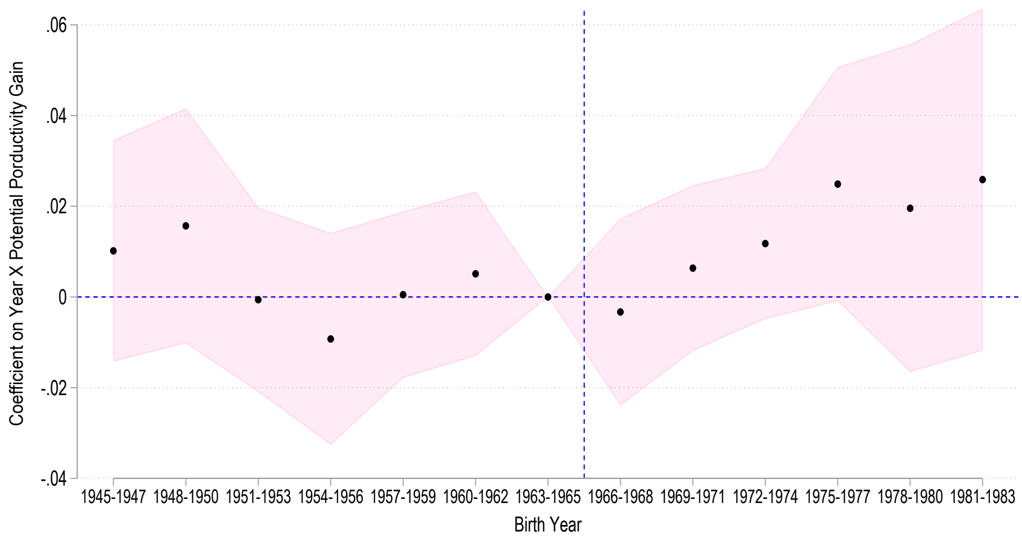
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using diabetes as the dependent variable. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at the year of birth. Shaded area indicates 90% confidence intervals.

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



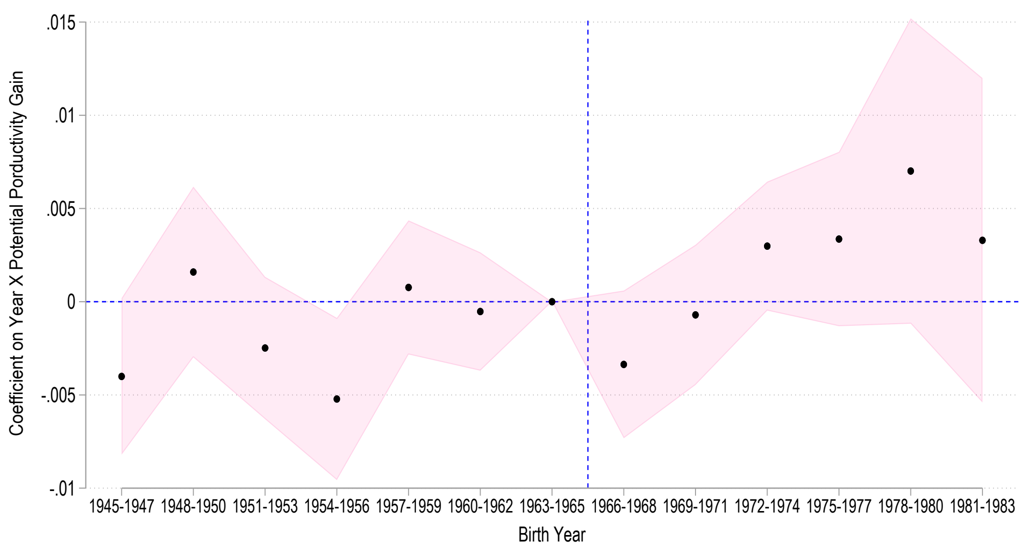
Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using hypertension as the dependent variable. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at the year of birth. Shaded area indicates 90% confidence intervals.

Figure A.14: Event study estimates of the effect of potential productivity gains on cognitive imbalance



Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using cognitive imbalance index as the dependent variable. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at the year of birth. Shaded area indicates 90% confidence intervals.

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



Notes: The figure plots the coefficients from estimating an event-study model (equation 4) using neurological issues as the dependent variable. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Those born between 1963 and 1965 are the reference category. The regression includes district of birth, year of birth fixed effects and ditstrict controls: total fertilizer exposure, precipitation and temperature at the year of birth. Shaded area indicates 90% confidence intervals.

Tables

Table A.1: Effect on number of crops

	Number of crops	
	(1)	(2)
ProdGain $\times$ Post^{1965}	-0.4***	-0.4***
	(0.06)	(0.07)
Observations	13566	13413
Mean of depvar	4.39	4.40
Year and District FE	Yes	Yes
Precipitation & Temperature	No	Yes
Geo. & SE controls x $\mathbf{I}\_t$	No	Yes
Yield controls (W,R)^{1957} x $\mathbf{I}\_t$	No	Yes
Area Share^{1957} x $\mathbf{I}\_t$	No	Yes

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

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

	Height Stunting	
	(1)	(2)
ProdGain × 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. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the year of birth. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.3: Effect of potential productivity gains on height: Controlling for baseline average road density of neighboring districts

	Height (cms)				
	(1)	(2)	(3)	(4)	(5)
	$\leq$ 100 km	$\leq$ 200 km	$\leq$ 300 km	$\leq$ 400 km	$\leq$ 500 km
ProdGain × Post^{1965}	-0.205**	-0.190**	-0.193**	-0.189**	-0.192**
	(0.083)	(0.077)	(0.077)	(0.077)	(0.077)
Observations	31632	37248	37248	37248	37248
Indv. controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	155.775	155.691	155.691	155.691	155.691

Notes: This table presents the results on the effects of exposure to potential productivity gains on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. All columns include individual controls, district controls for precipitation, temperature, and fertilizer exposure at the year of birth, as well as district and year of birth fixed effects. Each column represents a separate regression estimating equation (eq 3). Columns (1)-(5) utilize different cutoff distances for the road length metric of neighboring districts. Specifically, each column controls for the average road length of neighboring districts interacted with a linear cohort, with cutoff distances set at 100, 200, 300, 400, and 500 kilometers, respectively. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.4: Effect of potential productivity gains on metabolic syndrome: Controlling for baseline average road density of neighboring districts

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, and baseline average road length of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.5: Effect of potential productivity gains on cognitive imbalance: Controlling for baseline average road density of neighboring districts

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score(<15)	(4) Cognition Score(<19)
ProdGain × Post^{1965}	0.002	0.000	-0.003	0.004
	(0.007)	(0.001)	(0.005)	(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: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, and baseline average road length of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.6: Effect of potential productivity gains on motor deficit: Controlling for baseline average road density of neighboring districts

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.009	0.005	-0.000
	(0.011)	(0.005)	(0.003)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.029	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, and baseline average road length of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.7: Effect of potential productivity gains on height: Controlling for baseline rail network of neighboring districts

	Height (cms)				
	(1) $\leq$ 100 km	(2) $\leq$ 200 km	(3) $\leq$ 300 km	(4) $\leq$ 400 km	(5) $\leq$ 500 km
ProdGain × Post^{1965}	-0.143**	-0.137*	-0.138*	-0.134*	-0.134*
	(0.073)	(0.071)	(0.071)	(0.071)	(0.072)
Observations	36923	36923	36923	36923	36923
Indv. controls	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	155.704	155.704	155.704	155.704	155.704

Notes: This table presents the results on the effects of exposure to potential productivity gains on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. All columns include individual controls, district controls for precipitation, temperature, and fertilizer exposure at the year of birth, as well as district and year of birth fixed effects. Each column represents a separate regression estimating equation (eq 3). Columns (1)-(5) utilize different cutoff distances for the rail netwrok metric of neighboring districts. Specifically, each column controls for the average aseline average rail network (in miles) of neighboring districts interacted with a linear cohort, with cutoff distances set at 100, 200, 300, 400, and 500 kilometers, respectively. Standard errors are 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 metabolic syndrome: Controlling for baseline rail network of neighboring districts

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.010*	0.001	-0.002	0.014***	0.007**	-0.000	0.002
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Observations	40634	40634	40634	40634	40634	40634	40634
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.	-0.016	0.162	0.794	0.250	0.108	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, and baseline aseline average rail network (in miles) of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.9: Effect of potential productivity gains on cognitive imbalance: Controlling for baseline rail network of neighboring districts

	Cognitive Imbalance Index	Components		
	(1)	(2) Neuro issue	(3) Cognition Score($<$15)	(4) Cognition Score($<$19)
ProdGain $\times$ Post^{1965}	0.006	0.002	-0.001	0.001
	(0.007)	(0.001)	(0.004)	(0.003)
Observations	40634	40634	40634	40634
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	0.021	0.334	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, aseline average rail network (in miles) of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.10: Effect of potential productivity gains on motor deficit: Controlling for baseline rail network of neighboring districts

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain $\times$ Post^{1965}	0.010	0.006	-0.002
	(0.010)	(0.004)	(0.003)
Observations	40634	40634	40634
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	0.155

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics and include fixed effects for district and year of birth, precipitation, temperature, fertilizer exposure at the year of birth, and baseline average rail network (in miles) of neighboring districts within a 500-kilometer radius, interacted with a linear cohort variable. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Standard errors are in parentheses and clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.11: Gender-based heterogeneity: 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. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.12: Gender-based heterogeneity: Effect of potential productivity gains on metabolic syndrome

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

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

Table A.13: Gender-based heterogeneity: 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}	0.010	0.001	0.001	0.007**
	(0.007)	(0.001)	(0.004)	(0.003)
Female=1 $\times$ ProdGain $\times$ Post^{1965}	-0.008***	0.000	-0.003**	-0.007***
	(0.002)	(0.001)	(0.002)	(0.001)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

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

Table A.14: Gender-based heterogeneity: Effect of potential productivity gains on motor deficit

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

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

Table A.15: Family-condition based heterogeneity: Effect of potential productivity gains on height

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

Notes: This table presents the results on the effects of exposure to potential productivity gains on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 inlcudes district controls for precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. *Poor* is an indicator that denotes whether an individual was born into a low-income family. anStandard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.16: Family-condition based heterogeneity: Effect of potential productivity gains on metabolic syndrome

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. *Poor* is an indicator that denotes whether an individual was born into a low-income family. 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: Family-condition based heterogeneity: Effect of potential productivity gains on cognitive imbalance

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

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

Table A.18: Heterogeneity analysis: Effect of potential productivity gains on motor deficit

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

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

Table A.19: Religion-based heterogeneity: Effect of potential productivity gains on height

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

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

Table A.20: Religion-based heterogeneity: 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 × Post^{1965}	0.011**	0.001	0.003	0.015***	0.007**	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Hindu=1 × ProdGain × Post^{1965}	0.001	-0.001	-0.003*	0.003	0.001	0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Observations	41014	41014	41014	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

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

Table A.21: Religion-based heterogeneity: 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}	0.008	0.001	0.001	0.005
	(0.007)	(0.001)	(0.005)	(0.003)
Hindu=1 × ProdGain × Post^{1965}	-0.006**	0.000	-0.004*	-0.004**
	(0.003)	(0.001)	(0.002)	(0.002)
Observations	41014	41014	41014	41014
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

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

Table A.22: Religion-based heterogeneity: Effect of potential productivity gains on motor deficit

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

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

Table A.23: Effect of exposure to green revolution on migrating away from the birth-district

	(1) Migrated
ProdGain $\times$ Post^{1965}	0.007
	(0.004)
Observations	41014
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	0.261

Notes: The table reports the regression coefficient from an analysis examining the relationship between an individual's probability of migrating out of their birth district and potential productivity gains in wheat and rice, employing a difference-in-differences empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. 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: Heterogeneity analysis: Effect of potential productivity gains on height

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

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

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

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

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

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

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

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

Table A.27: Heterogeneity analysis: Effect of potential productivity gains on motor deficit

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

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

Table A.28: Effect of potential productivity gains on height controlling for adult behavior

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

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

Table A.29: Effect of potential productivity gains on metabolic syndrome controlling for adult behavior

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

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

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

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, adult behavior: smoking, alcohol consumption and exercise, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. 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.31: Heterogeneity analysis: Effect of potential productivity gains on motor deficit

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, adult behavior: smoking, alcohol consumption and exercise, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. 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.32: Effects of potential productivity gains on population characteristics and selective fertility

	(1) Share SC Female	(2) Share ST Female	(3) Share Adult Literate Female	(4) Mother Middle School Educated
ProdGain $\times$ Post^{1965}	0.0005	-0.0002	-0.0026	0.0014
	(0.0005)	(0.0006)	(0.0016)	(0.0017)
Observations	528	528	484	41,229
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Mean of dep. var.	0.079	0.044	0.054	0.022

Notes: This table presents the results on the effects of exposure to potential productivity gains on four diffrent outcomes from estimating equation 3. The dependent variables in columns (1)-(3) are population-level average characteristics in each district and year based on population censuses of 1961 and 1981. For Column (4), the dependent variable is an indicator of whether an individual's mother has middle-school education. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985, and the estimation includes individual controls (religion, caste, gender and rural birth), district and year of birth fixed effects. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.33: Worst-case scenario DID estimates of the effect on height using trimmed population

	Height (cms)
	(1)
ProdGain $\times$ Post^{1965}	-0.164**
	(0.077)
	[-0.32,-0.01]
Observations	37216
Indv. controls	Yes
District FE	Yes
YOB FE	Yes
District controls	Yes
Mean of dep. var.	155.693

Notes: This table presents the results on the effects of exposure to potential productivity gains on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. It is adjusted by trimming 0.675 percentage points from the sample of individuals born after 1966 in districts with above-average productivity gains, focusing on those from low-income families who are shorter than average for their gender or who exhibit metabolic syndrome, cognitive issues, or motor deficits. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also inlcudes district controls for precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. Bootstrapped 95% confidence intervals, calculated over 100 iterations, are presented. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.34: Worst-case scenario DID estimates of the effect on meatabolic syndrome using trimmed population

	Metabolic S Index	Components					
	(1)	(2) BMI	(3) WH-Ratio	(4) Hypertension	(5) Diabetes	(6) Chronic Heart	(7) Cholestrol
ProdGain $\times$ Post^{1965}	0.012**	0.000	0.001	0.017***	0.007**	-0.001	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
	[0.00,0.02]	[-0.01,0.01]	[-0.01,0.01]	[0.01,0.03]	[0.00,0.01]	[-0.00,0.00]	[-0.00,0.00]
Observations	40982	40982	40982	40982	40982	40982	40982
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.015	0.163	0.794	0.250	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. It is adjusted by trimming 0.675 percentage points from the sample of individuals born after 1966 in districts with above-average productivity gains, focusing on those from low-income families who are shorter than average for their gender or who exhibit metabolic syndrome, cognitive issues, or motor deficits. The models control for individual demographics, fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. Column 1 shows the effect for metabolic syndrome index. Cols (2)- (7) show the effect on incidence of different health indicators. Bootstrapped 95% confidence intervals, calculated over 100 iterations, are presented. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.35: Worst-case scenario DID estimates of the effect on cognitive imbalance using trimmed population

	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)	(0.005)	(0.003)
	[-0.01,0.02]	[-0.00,0.00]	[-0.01,0.01]	[-0.00,0.01]
Observations	40982	40982	40982	40982
Indv. controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
District controls	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.004	0.021	0.333	0.144

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. It is adjusted by trimming 0.675 percentage points from the sample of individuals born after 1966 in districts with above-average productivity gains, focusing on those from low-income families who are shorter than average for their gender or who exhibit metabolic syndrome, cognitive issues, or motor deficits. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district $\times$ year of birth level. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Bootstrapped 95% confidence intervals, calculated over 100 iterations, are presented. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.36: Worst-case scenario DID estimates of the effect on motor deficit using trimmed population

	Motor Deficit Index	Components	
	(1)	(2) Grip Strength Deficit	(3) Balance Deficit
ProdGain × Post^{1965}	0.013	0.007*	-0.001
	(0.010)	(0.004)	(0.003)
	[-0.01,0.03]	[-0.00,0.02]	[-0.01,0.00]
Observations	40982	40982	40982
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.028	0.396	0.156

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. It is adjusted by trimming 0.675 percentage points from the sample of individuals born after 1966 in districts with above-average productivity gains, focusing on those from low-income families who are shorter than average for their gender or who exhibit metabolic syndrome, cognitive issues, or motor deficits. The models control for individual demographics, fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district × year of birth level. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different health indicators. Bootstrapped 95% confidence intervals, calculated over 100 iterations, are presented. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.37: 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 and district of birth, precipitation, temperature and fertilizer exposure at the district × year of birth level. Standard errors are in parentheses and clustered at the district of birth. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.38: Effect of potential productivity gains on height

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

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

Table A.39: Effect of potential productivity gains on metabolic syndrome index

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, district of birth and year of birth fixed effects and dsitrict trends. 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.40: Effect of potential productivity gains on cognitive imbalance

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, district of birth and year of birth fixed effects and dsitrict trends. 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.41: Effect of potential productivity gains on motor deficit index

	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 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, district of birth and year of birth fixed effects and dsitrict trends. 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.42: Effect of potential productivity gains on height controlling for baseline share of urban population and service sector employment

	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 od the effects of exposure to potential productivity gains in wheat and rice on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline controls: share of urban population and share of service sector employment interacted with linear cohort. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.43: Effect of potential productivity gains on metabolic syndrome index controlling for baseline share of urban population and service sector employment

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline controls: share of urban population and share of service sector employment interacted with linear cohort. 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.44: Effect of potential productivity gains on cognitive imbalance controlling for baseline share of urban population and service sector employment

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline controls: share of urban population and share of service sector employment interacted with linear cohort. 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.45: Effect of potential productivity gains on motor deficit controlling for baseline share of urban population and service sector employment

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline controls: share of urban population and share of service sector employment interacted with linear cohort.Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different components of motor deficit. 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.46: Effect of potential productivity gains on height

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

Notes: This table presents the results od the effects of exposure to potential productivity gains in wheat and rice on height. The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline number of primary healthcare centres interacted with linear cohort. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.47: Effect of potential productivity gains on metabolic syndrome index

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline number of primary healthcare centres interacted with linear cohort. 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.48: Effect of potential productivity gains on cognitive imbalance

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression includes baseline controls: share of interacted with linear cohort. 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.49: Effect of potential productivity gains on cognitive imbalance

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1955-1985. The models control for individual demographics, and fixed effects for year and district of birth, temperature and fertilizer exposureat the district of birth $\times$ year of birth level. 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.50: Rural-urban heterogeneity analysis: effect of potential productivity gains on height

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

Notes: This table presents the results on the health effects of exposure to potential productivity gains. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. The regression also includes baseline number of primary healthcare centres interacted with linear cohort. Standard errors are clustered at the district of birth level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.51: 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 $\times$ Post^{1965}	0.013**	0.002	0.004	0.017***	0.007*	-0.001	0.002
	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)	(0.002)	(0.001)
Born in rural area=1 $\times$ ProdGain $\times$ Post^{1965}	-0.002	-0.002	-0.004***	0.001	0.000	0.001	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	41229	41229	41229	41229	41229	41229	41229
Indv. controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	-0.014	0.163	0.794	0.251	0.109	0.029	0.022

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. 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.52: 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 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. 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.53: 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 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year and district of birth, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. Column 1 shows the effect for motor deficit index. Cols (2)- (3) show the effect on incidence of different components of motor deficit. 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.54: Effects of Potential Productivity Gains on Household Food Expenditure Shares

	(1) Cereals	(2) Lentils	(3) Edible Oil	(4) Milk & Sugar	(5) Fruits & Vegetables	(6) Eggs, Meat & Fish
ProdGain $\times$ Post^{1965}	0.073	-0.008	0.010	0.096	-0.100	-0.070
	(0.123)	(0.073)	(0.090)	(0.134)	(0.113)	(0.114)
Observations	23639	23639	23639	23639	23639	23639
District FE	Yes	Yes	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	27.835	10.881	15.454	19.145	17.576	9.108

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of hosuehold head born between 1945-1985. The dependent variables in Columns (1)–(6) are the share of expenditure on each food group in a week in a household. The regression controls for fixed effects for district and year of birth. Cereal consists of rice, wheat, millets an their products. 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.55: Heterogeneity Analysis of Health Outcomes by Share of Cereal Expenditure

	(1) Height	(2) Hypertension	(3) Diabetes	(4) Grip Strength Deficit
ProdGain $\times$ Post^{1965}	-0.365***	0.005	0.008	0.004
	(0.112)	(0.005)	(0.005)	(0.005)
High Cereal Exp. Share=1 $\times$ ProdGain $\times$ Post^{1965}	0.000	0.003**	0.006***	0.002
	(0.043)	(0.001)	(0.002)	(0.002)
Observations	22201	24716	24716	24716
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
Mean of dep. var.	158.589	0.120	0.255	0.453

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of hosuehold head born between 1945-1985. The models control for fixed effects for district and year of birth. Columns 1–4 show the effect on height, incidence of hypertension, diabetes and grip strength deficit respectively. The second row shows the heterogenous effect of living in a housheold with high share of cereal expenditure in total expenditure. Cereal consists of rice, wheat, millets an their products. 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.56: Heterogeneity Analysis of Health Outcomes by Share of Pulse Expenditure

	(1) Height	(2) Hypertension	(3) Diabetes	(4) Grip Strength Deficit
ProdGain $\times$ Post^{1965}	-0.375***	0.005	0.009*	0.005
	(0.113)	(0.005)	(0.005)	(0.006)
High Lentils Exp. Share=1 $\times$ ProdGain $\times$ Post^{1965}	0.024	0.001	0.001	-0.002
	(0.041)	(0.001)	(0.002)	(0.002)
Observations	22201	24716	24716	24716
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
Mean of dep. var.	158.589	0.120	0.255	0.453

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of hosuehold head born between 1945-1985. The models control for fixed effects for district and year of birth. Columns 1–4 show the effect on height, incidence of hypertension, diabetes and grip strength deficit respectively. The second row shows the heterogenous effect of living in a housheold with high share of pulse expenditure in total expenditure. 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.57: Heterogeneity Analysis of Health Outcomes by Share of Meat, Egg and Fish Expenditure

	(1) Height	(2) Hypertension	(3) Diabetes	(4) Grip Strength Deficit
ProdGain $\times$ Post^{1965}	-0.303***	0.009	0.013**	0.004
	(0.114)	(0.005)	(0.005)	(0.006)
High Meat Exp. Share=1 $\times$ ProdGain $\times$ Post^{1965}	-0.074	-0.003*	-0.004	0.000
	(0.056)	(0.002)	(0.002)	(0.003)
Observations	22201	24716	24716	24716
District FE	Yes	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes	Yes
Mean of dep. var.	158.589	0.120	0.255	0.453

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of hosuehold head born between 1945-1985. The models control for fixed effects for district and year of birth. Columns 1–4 show the effect on height, incidence of hypertension, diabetes and grip strength deficit respectively. The second row shows the heterogenous effect of living in a housheold with high share of meat, egg and fish expenditure in total expenditure. 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.58: Effect of potenital productivity gains on per capita consumption of rice, wheat, and millet

	(1) Rice per person (kg)	(2) Wheat per person (kg)	(3) Millet per person (kg)
ProdGain $\times$ Post^{1965}	0.118*	0.044	0.001
	(0.061)	(0.033)	(0.001)
Observations	15691	15325	14637
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
Mean of dep. var.	14.500	6.668	0.019

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of hosuehold head born between 1945-1985 and living in households that purchase wheat, rice or millet from ration shops. The models control for fixed effects for district and year of birth of household's head. Cols (1)-(3) show the effect on consumption per person (kgs/30 days) of rice, wheat and millet. 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.59: Effects of Potential Productivity Gains on Nutritional Adequacy Ratios for Calories, Carbohydrates, and Protein

	Nutrition Adequacy Ratio		
	Cal	Carb	Protein
ProdGain $\times$ Post^{1965}	0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)
Observations	58045	58060	58489
HH controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
Mean of dep. var.	1.02	1.29	1.04

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample is derived from the 1999-2000 National Sample Survey on Household Consumption Expenditure and consists of households where the head was born between 1945 and 1985. The models control for the household head's religion, caste, household size, and household type, categorized by main occupation and whether the household is located in a rural or urban area. Fixed effects for the district of residence and year of birth are also included. Columns (1) through (3) report the estimated effects of potential productivity gains on the household's nutritional adequacy ratios for calories, carbohydrates, and protein. The nutritional adequacy ratio is calculated as the ratio of total calorie or nutrient intake to the household's recommended dietary intake, based on its composition and the guidelines provided by the National Institute of Nutrition. Standard errors are in parentheses and clustered at the district of residence level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.60: Effects of Potential Productivity Gains on Nutritional Adequacy Ratios for Micronutrients

	Nutrition Adequacy Ratio						
	Nutrition Index	Iron	Folate	Zinc	Vit B1	Vit B2	Calcium
ProdGain × Post^{1965}	-0.008	-0.003	-0.002	-0.003	-0.009***	-0.002	-0.003
	(0.007)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	51790	58022	59214	58200	58188	58433	58706
HH 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.	-0.05	0.69	1.08	0.89	0.94	0.51	0.57

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample is derived from the 1999-2000 National Sample Survey on Household Consumption Expenditure and consists of households where the head was born between 1945 and 1985. The models control for the household head's religion, caste, household size, and household type, categorized by main occupation and whether the household is located in a rural or urban area. Fixed effects for the district of residence and year of birth are also included. Columns (2) through (7) report the estimated effects of potential productivity gains on the household's nutritional adequacy ratios for iron, folate, zinc, vitamin B1, vitamin B2 and calcium. Column (1) presents the nutritional adequacy ratio for all micronutrients, constructed as a summary standardized index that aggregates information across all micronutrients. The nutritional adequacy ratio is calculated as the ratio of total calorie or nutrient intake to the household's recommended dietary intake, based on its composition and the guidelines provided by the National Institute of Nutrition. Standard errors are in parentheses and clustered at the district of residence level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.61: Effects of Potential Productivity Gains on Nutritional Adequacy Ratios for Micronutrients: Urban Households

	Nutrition Adequacy Ratio (Urban)						
	Nutrition Index	Iron	Folate	Zinc	Vit B1	Vit B2	Calcium
ProdGain × Post^{1965}	0.012	0.004	0.000	0.003	-0.004	0.004	0.005
	(0.014)	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.004)
Observations	21861	23964	23829	23807	24036	24137	24179
HH 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.	0.01	0.68	1.11	0.87	0.95	0.54	0.63

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample is derived from the 1999-2000 National Sample Survey on Household Consumption Expenditure and consists of households where the head was born between 1945 and 1985. The models control for the household head's religion, caste, household size, and household type, categorized by main occupation and living in urban area. Fixed effects for the district of residence and year of birth are also included. Columns (2) through (7) report the estimated effects of potential productivity gains on the household's nutritional adequacy ratios for iron, folate, zinc, vitamin B1, vitamin B2 and calcium. Column (1) presents the nutritional adequacy ratio for all micronutrients, constructed as a summary standardized index that aggregates information across all micronutrients. The nutritional adequacy ratio is calculated as the ratio of total calorie or nutrient intake to the household's recommended dietary intake, based on its composition and the guidelines provided by the National Institute of Nutrition. Standard errors are in parentheses and clustered at the district of residence level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.62: Effects of Potential Productivity Gains on Nutritional Adequacy Ratios for Micronutrients: Rural Households

	Nutrition Adequacy Ratio (Rural)						
	Nutrition Index	Iron	Folate	Zinc	Vit B1	Vit B2	Calcium
ProdGain $\times$ Post^{1965}	-0.017**	-0.006**	-0.002	-0.005*	-0.011***	-0.003	-0.005
	(0.008)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	29929	34058	35385	34393	34152	34296	34527
HH 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.	-0.10	0.69	1.06	0.90	0.93	0.50	0.52

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample is derived from the 1999-2000 National Sample Survey on Household Consumption Expenditure and consists of households where the head was born between 1945 and 1985. The models control for the household head's religion, caste, household size, and household type, categorized by main occupation and living in rural area. Fixed effects for the district of residence and year of birth are also included. Columns (2) through (7) report the estimated effects of potential productivity gains on the household's nutritional adequacy ratios for iron, folate, zinc, vitamin B1, vitamin B2 and calcium. Column (1) presents the nutritional adequacy ratio for all micronutrients, constructed as a summary standardized index that aggregates information across all micronutrients. The nutritional adequacy ratio is calculated as the ratio of total calorie or nutrient intake to the household's recommended dietary intake, based on its composition and the guidelines provided by the National Institute of Nutrition. Standard errors are in parentheses and clustered at the district of residence level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.63: 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 effects of potential productivity gains exposure on height. The potential productivity gains are calculated as a weighted sum of the potential gains in wheat and rice, where the weights are the HYV adoption rates of wheat and rice in South Asia, excluding India. The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. Column 1 shows the results with individual controls, district of birth and year of birth fixed effects, and column 2 also includes district controls for precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. Standard errors are in the paranthesis and clustered at the district level. *, **, and *** represent statistical significance at 10%, 5%, and 1% level.

Table A.64: Effect of potential productivity gains on metabolic syndrome index

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

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The potential productivity gains are calculated as a weighted sum of the potential gains in wheat and rice, where the weights are the HYV adoption rates of wheat and rice in South Asia, excluding India. 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 and district of birth, precipitation, temperature and fertilizer exposure at the district of birth $\times$ year of birth level. 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.65: 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	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: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The potential productivity gains are calculated as a weighted sum of the potential gains in wheat and rice, where the weights are the HYV adoption rates of wheat and rice in South Asia, excluding India. 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 and district of birth, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. Column 1 shows the effect for cognitive imbalance index. Cols (2)- (4) show the effect on incidence of different components of cognitive imbalance. 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.66: Effect of potential productivity gains on motor deficit

	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: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The potential productivity gains are calculated as a weighted sum of the potential gains in wheat and rice, where the weights are the HYV adoption rates of wheat and rice in South Asia, excluding India. 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 and district of birth, precipitation, temperature and fertilizer exposure at the district of birth × year of birth level. Column 1 shows the effect on motor deficit index. Cols (2)- (3) show the effect on incidence of different components of motor deficit. 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.67: Effect of potential productivity gains on agrochemical related health risks

	Agrochemical Health Risk	Components	
	(1)	(2) Respiratory	(3) Cancer
ProdGain × Post^{1965}	0.0126**	0.0048**	0.0003
	(0.006)	(0.002)	(0.001)
Observations	41014	41014	41014
Indv. controls	Yes	Yes	Yes
District FE	Yes	Yes	Yes
YOB FE	Yes	Yes	Yes
District controls	Yes	Yes	Yes
Mean of dep. var.	-0.009	0.052	0.006

Notes: Each parameter is from a separate regression of the outcome variable on potential productivity gains in wheat and rice using a difference in difference empirical design (eq 3). The sample comes from the LASI, 2017 and comprises of individuals born between 1945-1985. The models control for individual demographics, and fixed effects for year of birth, district, precipitation, temperature and fertilizer exposure at the year of birth. Column 1 shows the effect for composite measure of agrochemical related health risk. Cols (2)- (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.68: Heterogeneity analysis: Effect of potential productivity gains on agrochemical related health risks

	Agrochemical Health Risk	Components	
	(1)	(2) Respiratory	(3) Cancer
ProdGain × Post^{1965}	0.0089	0.0037*	0.0001
	(0.005)	(0.002)	(0.001)
Rural=1 × ProdGain × Post^{1965}	0.0062***	0.0020***	0.0003
	(0.002)	(0.001)	(0.000)
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.	-0.009	0.052	0.006

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