# The Green Revolution and Infant Mortality in India*

Prashant Bharadwaj† James Fenske‡ Namrata Kala§
Rinchan Ali Mirza¶

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Abstract

We use a difference in differences approach to show that the adoption of High Yielding Varieties (HYV) reduced infant mortality in India. This holds even comparing children of the same mother. The effects of HVY adoption on mortality is larger for rural children, boys, and low-caste children. While we are not able to explore mechanisms in depth, our evidence points to a limited role played by increased investments in early childhood health or selection into childbearing in response to HYV adoption.

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†University of California San Diego. prbharadwaj@ucsd.edu. prbharadwaj.wordpress.com
‡University of Warwick. j.fenske@warwick.ac.uk. jamesfenske.com
§Massachusetts Institute of Technology. kala@mit.edu. namratakala.com
¶University of Kent. R.A.Mirza@kent.ac.uk. sites.google.com/site/rinchanmirza/home

## 1 Introduction

Between 1960 and 2000, India's infant mortality rate dropped from 163.8 per 1,000 live births to 66.6 per 1,000 live births. This impressive decline took place during the same decades in which India made astounding gains in agricultural productivity from 0.86 tons per hectare for wheat in 1960 to 2.79 tons per hectare in 2000, in large part due to research and implementation efforts that took place during the Green Revolution. By examining the relationship between agricultural productivity gains and infant mortality, this paper sheds new light on the intersection of two major developments in India and also extends prior work that has identified several factors behind poor child health outcomes across the developing world: inadequate health care seeking and participation by distressed mothers in the labor market (Bhalotra, 2010), *in utero* factors (Currie and Vogl, 2013), low levels of public expenditure on health infrastructure (Paxson and Schady, 2005; Cutler, Knaul, Lozano, Méndez, and Zurita, 2002; Maluccio et al., 2005) and lower per capita income (Pritchett and Summers, 1996), among others. Our analysis stretches from 1966 to 1998 and covers much of India, allowing us to examine the impacts of these gains for a country where agriculture is the main source of income for a large fraction of the population.[1]

Our study focuses on perhaps the single most important source of agricultural productivity gains: the adoption of high-yielding varieties (HYV) of seeds. The adoption of HYV began in the late 1960s in India with the advent of the Green Revolution and has continued ever since. The gains from HYV adoption are documented in the literature on the Green Revolution (e.g. Evenson and Gollin (2003a)). In this paper, we show the reduced form relationship between HYV adoption and infant mortality across districts of India over time. In particular, a one standard deviation increase in the share of cultivated area planted to HYV in a child's year of birth reduces infant mortality by 0.50 percentage points. This is substantial relative to the average infant mortality over births of 9.5% in our sample.

Our empirical strategy addresses standard concerns that can arise in examining the effect of HYV adoption on infant mortality. For instance, individuals might sort into high HYV adoption districts based on the characteristics of those districts. If the characteristics that are associated with sorting also affect infant mortality, then this could bias our results. Furthermore, individuals born in different years could be subjected to economic events,

[1]According to the FAO, some 70% of rural Indian households depend on agriculture for their main source of income. See http://www.fao.org/india/fao-in-india/india-at-a-glance/en/

such as recessions, which could drive part of the correlation between HYV adoption and infant mortality. To address these concerns, our baseline specification includes district fixed effects that absorb all time-invariant characteristics of the district that are associated with HYV adoption and also affect infant mortality. It also includes year of birth fixed effects that account for any shocks to infant mortality, such as recessions, that coincide with the year of birth but affect macroeconomic conditions beyond the level of a district. We also include, in alternative specifications, state-specific linear time trends or state by year fixed effects in our baseline estimates. The first takes into account any unobserved trending variables that may vary by state-specific birth cohorts, and the second accounts for any annual pattern in birth outcomes that may differ across states.

Our baseline specification, therefore, compares two children from the same district who are subjected to different levels of HYV adoption based on their years of birth, over and above any unobserved shocks to infant mortality that vary by the year of birth, and any long-run trends (or annual patterns) in infant mortality in the state of birth.

To uncover the mechanisms through which HYV adoption affects infant mortality, we use three different strategies. First, we examine heterogeneity in the effect of HYV adoption across various sub-groups. We find that HYV adoption has a greater effect on children born to mothers who were married younger and who have less education, i.e. mothers whose characteristics predict greater child mortality. The effect is also greater for a child born to a low-caste mother, which suggests that children from poorer households are helped more by HYV adoption. However, the effect is smaller when the child born is a girl. Finally, the effect is greater for a child born in a rural area, implying that the effect of HYV adoption was primarily mediated through agricultural incomes and general development of rural areas.

Next, we examine whether early childhood investments, which might increase due to exposure to the Green Revolution, can explain part of the effects we observe. We find no evidence that such investments mediate the effect of HYV adoption on infant mortality; hence, rural health infrastructure that might correlate with the Green Revolution might not have played an important role in this instance. Finally, we investigate whether HYV adoption affects infant mortality by influencing the profile of mothers who give birth. We find little evidence that predetermined maternal or child characteristics respond to HYV adoption.

One of the greatest limitations of this paper is the lack of a clean natural experiment, which would allow for truly exogenous variation in HYV adoption across districts. Districts in India are large, and even though we exploit variation due to spread of HYV within a district over time, concerns about how states allocate funds to districts for projects that could be correlated with investments in Green Revolution (such as schooling and infrastructure) are first order. In order to move the needle towards a causal interpretation, we carry out several empirical exercises to show the robustness of our baseline results. First, we show that replacing district fixed effects with mother fixed effects gives results that are close to the baseline estimates. That is, when comparing two children born to the same mother, the child whose birth coincided with a greater prevalence of HYV cultivation is more likely to survive. Then, we address the concern of broad secular trends in infant mortality at the district level influencing our results. To do so, we carry out two empirical exercises. The first involves including district-specific linear time trends in our baseline specification and showing that our results do not change in terms of sign or significance. The second involves using an event-study specification that interacts eventual HYV adoption at the district level with year fixed effects to show that there are no differential time trends in infant mortality prior to the Green Revolution. We carry out several other robustness tests, which form the bulk of the analyses presented in the Appendix.

We contribute to the broader literature on the microeconomics of technology adoption. For example, there are cross-country studies that analyze the social, economic and political impacts of technology adoption across both agricultural and non-agricultural sectors. Nunn and Qian (2011) examine the effects of potato adoption in Europe, and Bustos, Caprettini, Ponticelli, et al. (2016) investigate the impact of agricultural productivity gains on non-agricultural economic activity. There are also more focused studies examining whether agricultural science and research impact economic or social outcomes at a smaller geographical scale (Hornbeck and Keskin, 2014; Fan, Zhang, and Zhang, 2000; Meinzen-Dick, Adato, Haddad, and Hazell, 2003; Dalrymple, 2008). Finally, the literature identifying sources of child health outcomes is also well developed (Bhalotra, 2010; Maluccio et al., 2005; Paxson and Schady, 2005; Cutler, Knaul, Lozano, Méndez, and Zurita, 2002; Pongou, Salomon, and Ezzati, 2006).

However, to our knowledge, very few studies exist that connect productivity gains from agricultural technology adoption to child health outcomes in micro-economic data. The first contribution of this paper is, therefore, to add critical evidence in this space by examining the impacts of HYV adoption on infant mortality in India. In that regard, this paper is similar to the work of Barnwal, Dar, von der Goltz, Fishman, McCord, and Mueller (2017), who use geospatial data from multiple countries in the Demographic Health Surveys to examine how adoption of modern crop varieties affects infant mortality globally. Barnwal et al.'s results for South Asia suggest that complete coverage by modern varieties would reduce infant mortality by 22 percent, while our results would have that number at around 27 percent. Another related paper is the work of Brainerd and Menon (2014) who examine the specific relationship between fertilizer agrichemicals in water and child health in India. Since the use of HYV seeds is typically accompanied by increased fertilizer use, in light of the findings of Brainerd and Menon (2014), we interpret our results as being net of the effects of fertilizer use.

The rest of the paper is organized as follows. In Section 2 we provide the background to our study. In particular, we document the development of the HYV of two major crops–wheat and rice–and their diffusion in India. We also postulate mechanisms that link HYV adoption to health outcomes. Section 3 describes the infant mortality data, the HYV data and the procedure we use to match the infant mortality data to the HYV data. Section 4 outlines our empirical strategy. Section 5 discusses our results. Section 6 investigates mechanisms linking HYV adoption to infant mortality. Section 7 reports robustness exercises. Section 8 concludes.

## 2 Background

The Green Revolution can be credited to the cross-breeding experiments of the International Rice Research Institute (IRRI), set up in the Philippines in 1961, and its sister institution, the International Centre for Maize and Wheat Improvement (CIMMYT) that was set up in Mexico in 1967 (Gollin, Hansen, and Wingender, 2016, p. 4). The development of hybrid varieties of wheat happened around the same time as that of rice. Cross-breeding experiments were initiated at the Rockefeller Foundation program for wheat improvement in Mexico, the precursor of CIMMYT, and by 1961 the first semi-dwarf varieties of the crop were released worldwide. Rice and wheat HYV were more successful in raising productivity than the HYV of other crops. For instance, yield increases from HYV adoption in crops such as sorghum and millet were smaller than those for rice and wheat (Estudillo and Otsuka, 2013, p. 22). This was because scientists had already developed a critical mass of knowledge about rice and wheat in particular, which did not exist for other crops (Evenson and Gollin, 2003a; Pingali, 2012). Gollin, Hansen, and Wingender (2016) state that

> in spite of the rapid success of the research in rice and wheat it took much longer for the Green Revolution to be extended to other crops, reflecting large differences in the initial stock of scientific knowledge.

Once the HYV of rice and wheat were introduced in India in 1965, their adoption was fairly rapid in the northern states. For instance, the share of cultivated area planted to HYV of rice in North India went from an average of 11% in 1965-69 to an average of 82% in 1975-79 (Barker, Herdt, and Rose, 1985, p. 218). Similarly, the share of cultivated area planted to wheat HYV also went up from an average of 10% to an average of 81% in the same region over the same period.[2] Such figures represent a sudden and sharp increase in HYV adoption on historical timescales. The success of HYV was markedly different in states outside North India where diffusion was both gradual and highly variable. For instance, in the primarily rain-fed states of eastern India – Western Bengal, Bihar and Orissa – the share of HYV acreage for rice averaged only around 25% during the early stages of the Green Revolution (Barker, Herdt, and Rose, 1985, p. 149).

An important reason behind the variable rates of HYV adoption was the differing prevalence of input factors. The northern states have an extensive canal irrigation network dating back to the colonial era and are characterized by uniform growing conditions that were suitable to adoption of earlier HYV of rice and wheat. The rest of the country relied primarily on rain-fed agriculture and was characterized by widely different agro-climatic conditions that made adapting the first generation HYV to local conditions more difficult. Another input factor that increased in salience after the mass electrification of Indian villages from the 1960s onwards was groundwater aquifers. Mass electrification increased the use of tube well irrigation that relied on access to groundwater aquifers. Since tube well irrigation gave farmers maximum control over both the timing and quantity of the water supply, access to groundwater aquifers became a crucial input into the successful adoption of HYV (D'Agostino, 2017).

Several crop-specific factors also contributed towards variation in diffusion rates. For instance, the early rice varieties previously were particularly susceptible to attacks of numerous diseases and pests (Pingali, Moya, and Velasco, 1990). They were also quite sensitive to unobserved managerial skill that hampered diffusion by restricting informa-

[2] These numbers are based on calculations we made using data from our sample.

tion flows between farmers (Munshi, 2004). In contrast, the early wheat varieties were not only adaptable to location-specific characteristics such as diseases, pests, and non-living stressors such as drought and temperature (Evenson and Gollin, 2003a) but also required less managerial expertise for their successful adoption (Munshi, 2004). It was due to such factors that there was a considerable delay between the adoption of wheat and rice HYV across India (Munshi, 2004).

Finally, factors such as income, investment, human capital, and agricultural policies also mattered for differential adoption rates (Gollin, Hansen, and Wingender, 2016, p. 11). In the appendix, we identify the cross-sectional correlates of HYV adoption in our sample at five points in time: 1966, 1970, 1975, 1980, 1985. HYV adoption was more widespread in districts with greater aquifer thickness and topsoil thickness, neutral pH, a handful of soil types, lower latitudes and, in some specifications, greater initial shares planted to wheat and rice. In a robustness exercise, we explicitly control for the possibility of these determinants being responsible for differential trends in infant mortality across districts.

A number of possible mechanisms connect HYV adoption to health outcomes. First is an increase in food production due to the higher productivity of HYV. Total cereal production in India increased by 33% going from 70 million tons to 93 million tons between 1961 and 1970 (Borlaug, 2002). Such an increase in cereal production decreased food prices, resulting in higher caloric intake. A higher caloric intake in turn led to gains in health and life expectancy. The health gains were especially acute for children. Evenson and Gollin (2003a) credit the productivity gains from HYV adoption with raising the health status of between 32 to 42 million pre-school children, and with lowering infant and child mortality worldwide.

A second possible mechanism is an increase in agricultural incomes earned from productivity enhancements through HYV adoption. The adoption of HYV led to substantial increases in the GNP of India in the late 1960s (Borlaug, 2002). Income can affect child health in several ways – for example, it can reduce the opportunity cost of maternal time, thereby causing mothers to seek health care services. A positive income shock can also lower distress labor market participation[3] of mothers and improve prospects of health in early life (Bhalotra, 2010). Finally, an increase in incomes can induce parental investments in child health either in the form of 'compensatory' or 'reinforcing' behavior

[3]Distress labor market participation of mothers is defined as maternal labor supply during recessions for the purpose of consumption smoothing (Bhalotra, 2010).

once child quality is revealed (Almond and Mazumder, 2013; Bharadwaj, Eberhard, and Neilson, 2017).

A third possible mechanism is an increase in human capital resulting from the adoption of HYV. The introduction of HYV in India has been shown to have led to greater private investments in schooling, average increases in levels of schooling, and an expansion of schooling infrastructure (Foster and Rosenzweig, 1995, 1996). Human capital can affect child health through a number of potential pathways. Educated parents, especially literate mothers, have been shown to be better managers of health issues, ranging from understanding and processing health information to implementation of at-home therapies (Dexter, LeVine, and Velasco, 1998; LeVine, LeVine, Schnell-Anzola, Rowe, and Dexter, 2011; Schnell-Anzola, Rowe, and LeVine, 2005; LeVine and Rowe, 2009; LeVine, LeVine, Rowe, and Schnell-Anzola, 2004). At a community level, higher literacy can contribute to improvements in child health through informational spillovers that involve literate adults lending "their skills to other family members, friends, or neighbors by reading prescription side effects or explaining instructions" (Smith-Greenaway, 2017, p. 308).

The profile of mothers who give birth can be linked to income shocks in such a way so as to reduce infant mortality. In particular, a decrease in income can cause high-risk mothers to delay their fertility decisions (Dehejia, Lleras-Muney, et al., 2004). Finally, a negative income shock can cause a dramatic collapse in public expenditures on health and, thereby, adversely affect child health outcomes (Paxson and Schady, 2005; Cutler, Knaul, Lozano, Méndez, and Zurita, 2002; Maluccio et al., 2005).

# 3 Data

In this section, we describe the data sources that were used in the empirical analysis. Moreover, where necessary, we describe the construction of the main variables in the analysis.

## 3.1 Adoption of HYV

### 3.1.1 Village dynamics in south asia

We take the annual data on the area planted to HYV from the Village Dynamics in South Asia (VDSA) dataset. The VDSA dataset is a panel that covers 281 districts across nineteen states of India over the period 1966 to 2009. It includes annual district-level information on the area (in hectares) planted to high-yielding varieties of six major crops–wheat, rice, maize, sorghum, finger millet, and pearl millet. Additionally, it has annual information on area cultivated (in hectares) and production (in tons) for 5 major and 19 minor crops. Aside from the data on agricultural outcomes, the VDSA dataset also has information on socioeconomic, climatic, soil, and agro-ecological variables. The nineteen states covered in the dataset are Assam, Himachal Pradesh, Kerala, Chhattisgarh, Jharkhand, Uttarakhand, Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal. The base year for districts in the VDSA panel is 1966. This means that data from child districts formed after 1966 are assigned to their respective parent districts to form a comparable sample of districts from 1966 to 2009 that is based on the 1966 district boundaries.

To compute our main explanatory variable – the adoption of HYV – we aggregate the area planted to HYV of all the major crops in each district in the year of birth. We then divide the sum by the total area cultivated in the district in the year of birth in order to compute the share of cultivated area planted to HYV.

### 3.1.2 Indian agriculture and climate

The Indian Agriculture and Climate Dataset (IACD) is a panel that covers 271 districts across thirteen states of India. Like the VDSA panel it has annual district-level data on the area planted to high-yielding varieties in hectares of the five major crops for the period 1957 to 1987. Since the IACD starts from 1957 this means that it has annual data on agricultural outcomes for several years before the introduction of HYV in the late 1960s. The states covered by the IACD are Haryana, Punjab, Uttar Pradesh, Gujarat, Rajasthan, Bihar, Orissa, West Bengal, Andhra Pradesh, Tamil Nadu, Karnataka, Maharashtra and Madhya Pradesh.

We use the same procedure we followed for the VDSA dataset to compute our main explanatory variable. First, we sum the area planted to HYV of all the major crops in each district in the year of birth. Then, we divide the sum by the total area cultivated in each district in the year of birth to compute the share of cultivated area planted to HYV.

## 3.2 Infant Mortality

### 3.2.1 Demographic and health survey data

The data on our outcomes of interest come from two rounds of the Demographic Health Surveys conducted in India in 1992-93 and 1998-99, respectively.

The data in the DHS surveys come in three formats:

1. The *Individual Recodes* survey women who are aged between 15 and 49. These are nationally representative surveys that contain information on several variables that we use. These include the woman's year of birth, her level of education, whether she lives in a rural area, her age, her caste, and her religion.

2. The *Births Recodes* are the complete birth histories of the women surveyed in the individual recodes. We use these data for our baseline results. Specifically, we use the child's year of birth, birth order, an indicator for a multiple birth, a dummy for female, and the length of the child's life. The recodes have births as far back as the 1950s, several years before the first year in which the data on HYV of crops starts in the VDSA dataset in 1966.

3. The *Children's Recodes* include more information on a smaller sample of children. Women are asked about births in the previous five years. There is information on early life investments such as vaccinations and breastfeeding. There is also information on prenatal investments including care from doctors and the circumstances of the child's birth. We use all of these variables in our empirical analysis.

### 3.2.2 Vital Statistics of India

An alternative source of data on infant mortality that we use is the annual Vital Statistics of India reports. These reports contain information on registered live births, deaths, infant deaths and stillbirths for each district, broken down by locality (i.e. rural or urban) and gender. We use the number of infant deaths and the number of births to compute our measure of infant mortality at the district level. The formula we use to compute our infant mortality measure is as follows:

$$\text{Infant Mortality Rate}_{dy} = \frac{\text{No. of infant deaths in district (d) in year (y)}}{\text{No. of live births in district (d) in year (y)}} \times 1000 \quad (1)$$

Our analysis uses annual data on the number of infant deaths and the number of births for the period from 1957 to 1993.

### 3.3 Additional controls

We use both average monthly rainfall in millimeters and average monthly temperature in degrees Celsius in a child's year of birth as controls. These are obtained from Matsuura and Willmott (2009). The annual data upon which our averages for rainfall and temperature are based covers the whole period of our panel from 1966 to 1999.

### 3.4 Matching DHS to HYV data

We use the names of the districts surveyed in the DHS to assign each child the share of HYV acreage of the district where the child was born. Where districts have split in the DHS but not in the VDSA data, children are assigned the agricultural data values from the parent district. Because the HYV acreage numbers reported in the VDSA data for one district in 1986 (The Dangs) are implausibly large relative to total acreage, we drop these observations from the data.

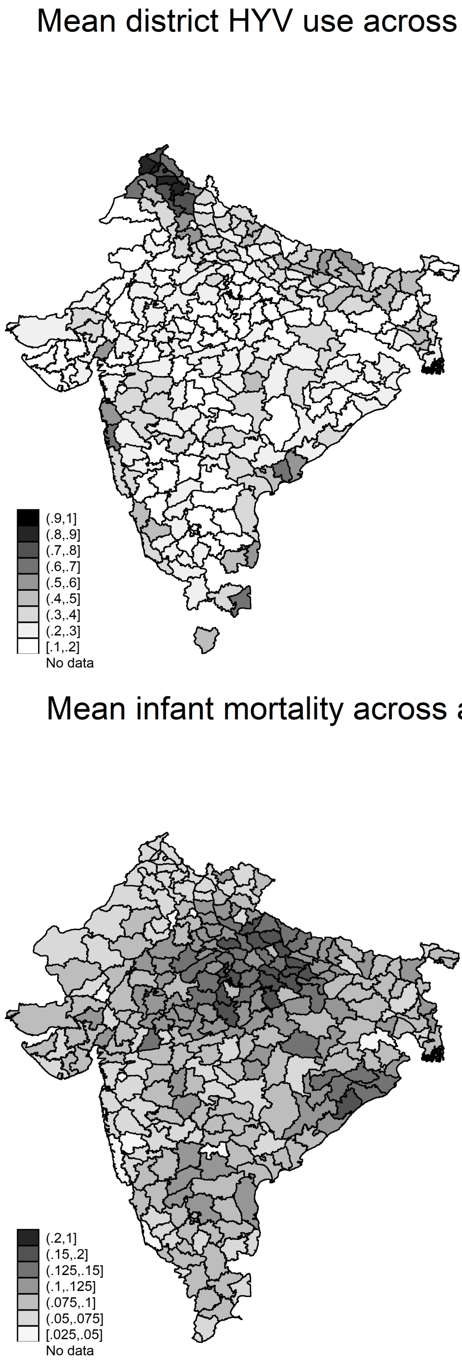
Using the above matching procedure we are able to match 76% of the total number of districts in the DHS dataset to districts in the VDSA dataset.

### 3.5 Summary statistics

We show the summary statistics used in this paper in Table 1. Infant mortality over births in our data averages 9.5%. The average for child mortality over births is higher at 13%. The share of HYV acreage averages 29% across the births in the sample. As Figure 1 shows there is substantial heterogeneity in HYV adoption and infant mortality across districts in our panel. Moreover, there is an inverse relationship between HYV adoption and infant mortality: districts with the lowest mean infant mortality over births are also the ones that have the highest mean shares of HYV acreage over births.

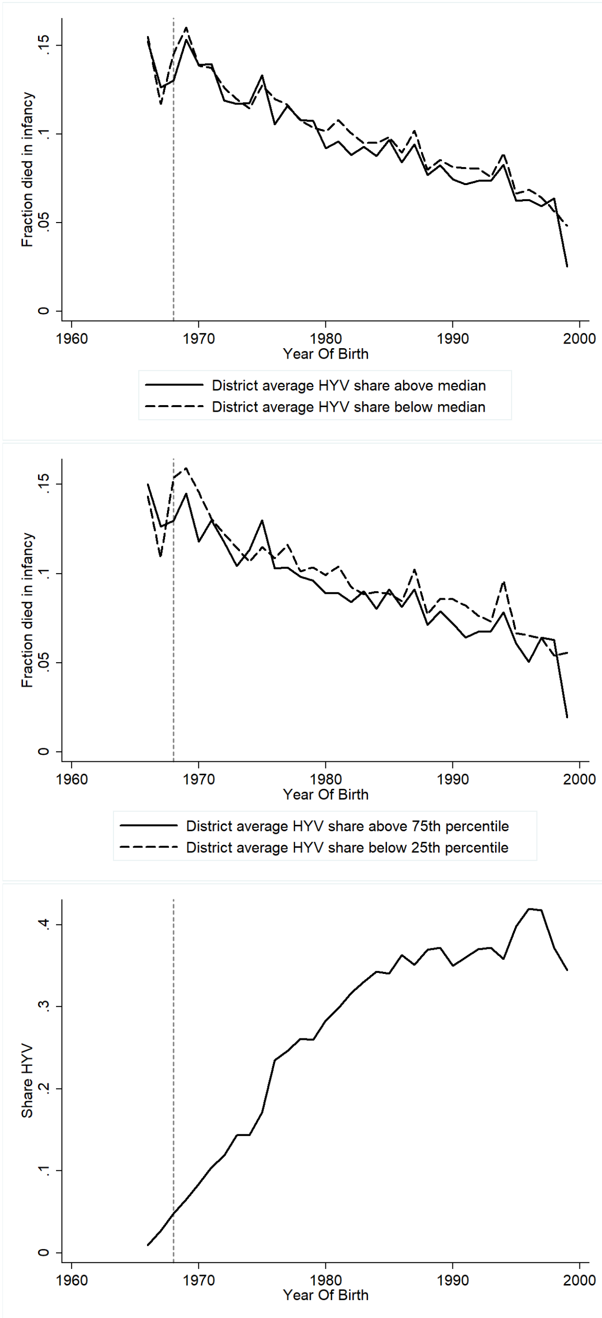
Table 1 also provides information on the characteristics of mothers in our sample. The average age of mothers in the sample is 34 years and the average birth order is nearly 3, meaning that a typical child in the data is a mother's third birth. Also, mothers have low levels of education (an average of 2.17 years) and tend to marry young (an average age of 16.2 years). In our baseline results we control for maternal characteristics, such as a mother's education, age, religion and caste, since they can influence infant mortality.

Figure 1: HYV adoption and Infant Mortality: Heterogeneity




*Notes*: The datasource used for 'mean district HYV use across all births' is the ICRISAT Village Dynamics in South Asia dataset. The period over which the 'mean district HYV use across all births' is calculated is 1966-1999. The datasources used for 'mean infant mortality across all births' are the Demographic Health Surveys (India) of 1992-93 and 1998-99. The period over which the 'mean infant mortality across all births' is calculated is 1954-1999.

FIGURE 2: HYV adoption and Infant Mortality: Trends




*Notes*: We use two alternative definitions for distinguishing between High and Low-HYV districts. In the first we define a High (or Low) HYV district in a given year as being one where the fraction of cultivated area planted to HYV is above (or below) its median value in that year. In the second we define a High (or Low) HYV district in a given year as being one where the fraction of cultivated area planted to HYV is above its 75th percentile (or below the 25th percentile) value in that year. The vertical line is at 1968 which we mark as the start of the Green Revolution.

A full description of all variables we constructed for our empirical analysis is provided in Table 2.

Additionally, Figure 2 shows declining infant mortality across both high and low-HYV adoption districts over the period 1966 to 1998. The trend is indicative of there being no systematic differences in infant mortality between high and low-HYV adoption districts prior to the introduction of HYV in the late 1960s. After these are introduced, a visible gap opens up between the infant mortality rates of the two sets of districts.

# 4 Empirical strategy

## 4.1 Event-Study Specification

As mentioned in Section 1, we make use of an event-study specification in order to rule out any pre-existing trends in infant mortality when estimating the impact of HYV adoption on infant mortality. The event-study specification we implement uses an alternative source of data on infant mortality that stretches back to 1951 (almost 18 years before the start of the Green Revolution in 1968) and takes the following form:

$$Mortality_{sdy} = \Gamma_y(Year_y \times ShareHYV_{d,r}) + \delta_d + \zeta_{sy} + \epsilon_{sdy} \tag{2}$$

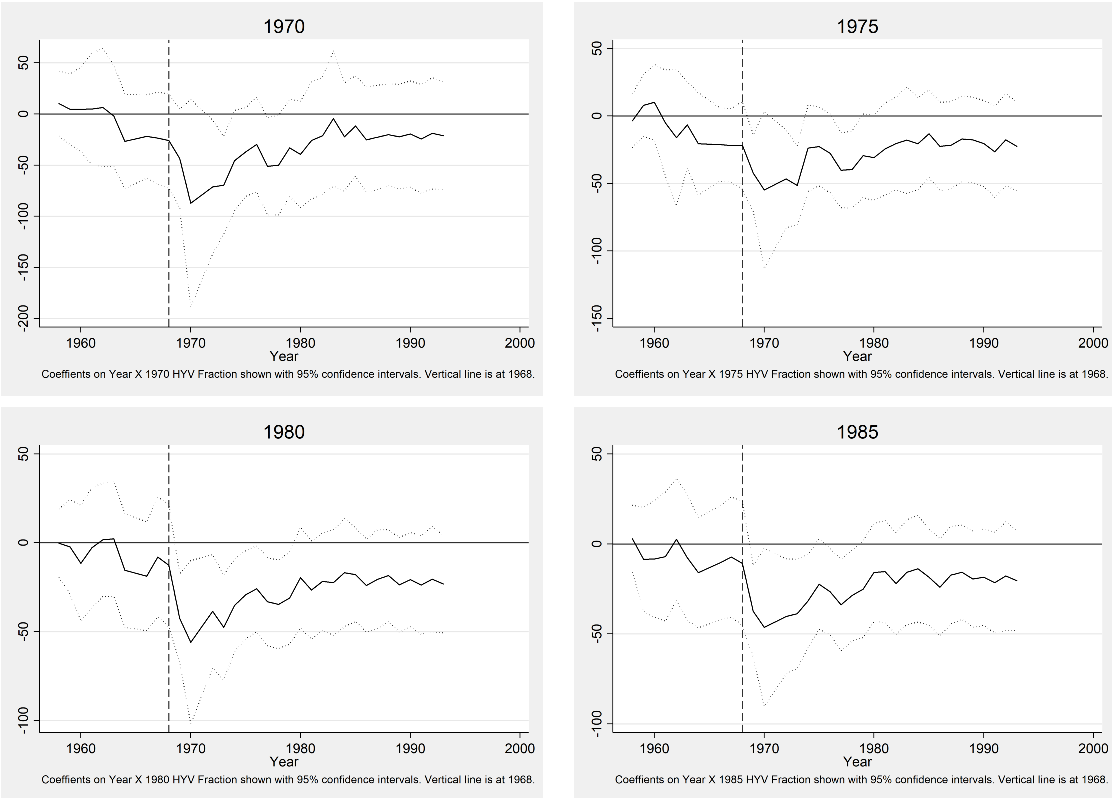
Here, $Mortality_{sdy}$, is the number of infant deaths per 1000 live births in district $d$ in state $s$ in year $y$. $(Year_y \times ShareHYV_{d,r})$ are the interactions between year dummies and the fraction of land planted to HYV in district $d$ in a reference year $r$. We report estimates for $r \in \{1970, 1975, 1980, 1985\}$. $\delta_d$ are district fixed effects, and $\zeta_{sy}$ are state-by-year fixed effects. We cluster our standard errors at the district level. $\Gamma_y$ is the vector of estimated interaction coefficients that reveal the relationship between HYV adoption and infant mortality in each year. If, for instance, the adoption of HYV from the Green Revolution reduced infant mortality, then we would expect the estimated coefficients to be more or less constant over time for the years before the Green Revolution and then to decline sharply after the start of the Green Revolution. Note also that since $ShareHYV_{d,r}$ is time-invariant and because equation (3) includes state by year fixed effects, the estimated $\Gamma_y$ coefficients must be measured relative to a baseline year, which we take to be 1957, the first year of data.

In Figure 3 we show the results from estimating our event-study specification in equation 3. Our purpose in estimating the event-study specification is to provide evidence for the lack of pre-trends in infant mortality between areas where HYV adoption was higher or lower before the Green Revolution. Figure 3 consists of four separate plots with each plot showing a variation of the same event-study specification. To create the plots we interact year of birth dummies with our measure for Green Revolution intensity (i.e. fraction of land planted to HYV in 1970, 1975, 1980, or 1985) and plot the resulting year and Green Revolution intensity interaction coefficients and their associated confidence intervals.

The identifying assumption in our regression specification with state-by-year fixed effects is that no omitted variables exist that correlate with both our HYV measure and with child mortality, that vary over time within districts, and that vary differentially across districts within a given state in a given year. One possible violation of this assumption would be differential district trends: if districts that would later become intense adopters of HYV were already on faster trends of mortality reduction prior to the start of the Green Revolution, these trends could continue after the start of the Green Revolution, leading to differential mortality outcomes for these districts even conditional on state-by-year fixed effects. That the gap in mortality widens between high-HYV and low-HYV districts only after the start of the Green Revolution is evidence in support of this identifying assumption.

It is clear from the figure that the fraction of land planted to HYV is uncorrelated with trends in infant mortality prior to the Green Revolution. We mark 1968 as the start of the Green Revolution in these figures, since that was the first year in which the fraction of cropped acreage planted to HYV surpassed 5% in the World Bank's India Agriculture and Climate Data Set. There is a decline in infant mortality starting around the start of the Green Revolution and that is most pronounced in the districts where HYV adoption is more widespread. The rapid decline after 1968 in the districts with greater adoption of HYV by 1970 is accounted for precisely by the fact that these districts were rapid adopters of the new varieties. This suggests that areas where the Green Revolution was more intense were not on a different trajectory in terms of their infant mortality compared to areas where the Green Revolution was less intense prior to the Green Revolution. Moreover, it was only around the time of the Green Revolution that infant mortality declined more rapidly in areas where Green Revolution was more intense. The apparent convergence between early adopters and other districts over time can be explained by the later adoption of HYVs in these districts, other sources of falling infant mortality that were common across all of India, and the greater marginal impact of interventions when aggregate mortality is greater.

Figure 3: HYV fraction and infant mortality




*Notes*: This figure plots interaction coefficients and confidence intervals from a regression where year of birth dummies are interacted with the fraction of land planted to HYV in the stated year. The regression controls for district fixed effects, year fixed effects, and state-by-year fixed effects.

## 4.2 Baseline Specification

In order to test for the impact of HYV adoption on infant mortality, we use ordinary least squares (OLS) to estimate the following reduced form equations:

$$Mortality_{isdy} = \beta ShareHYV_{dy} + x'_{isdy}\gamma + \eta_y + \delta_d + \zeta_s \times y + \epsilon_{isdy} \tag{3}$$

and

$$Mortality_{isdy} = \beta ShareHYV_{dy} + x'_{isdy}\gamma + \eta_y + \delta_d + \zeta_{sy} + \epsilon_{isdy} \quad (4)$$

Here, $Mortality_{isdy}$ is an indicator for the death of child $i$ in the first twelve months after birth, born in year $y$, whose mother is surveyed in district $d$ in state $s$. In our main results $ShareHYV_{dy}$ is the fraction of all cultivated land in district $d$ that is planted to HYV in the year of birth $y$. It measures the extent of HYV adoption in district $d$ in the year of birth $y$. $\beta$ is the coefficient of interest, and we expect its sign to be negative. Additionally, we include several important sets of fixed effects. The first are district fixed effects, $\delta_d$, that control for all time-invariant characteristics of the district. For instance, if a district has a lower level of HYV adoption as well as higher infant mortality due to its bad soil quality, then to obtain better estimates of the effect of technology on infant mortality we need to be able to control for the influence of the poor soils. A fixed effect at the district level would not only control for the influence of the soil quality, but would also capture all other time-invariant characteristics. The second set of fixed effects we include are year of birth fixed effects, $\eta_y$, that account for any time-specific shocks, such as economic recessions, that affect all districts equally in the year of birth.

In addition to the above fixed effects we also include either state-specific linear time trends, $\zeta_s \times y$ in equation (1), or state by year fixed effects, $\zeta_{sy}$ in equation (2), in our baseline specification.[4] The first accounts for possible unobserved trending variables that may vary by state-specific birth cohort, and the second accounts for general annual variation in birth outcomes that may vary across states. Finally, we cluster standard errors by district. In particular, we aggregate districts to those that existed in 1966, merging together districts that were split after the start of our principal data on HYV.

Hence, for identification, we compare children from the same district who are exposed to varying levels of HYV by virtue of their dates of birth, over and above any unobserved shocks to mortality that vary by year of birth, and any long-run trends (or annual patterns) in that child's state of birth. In our specification with state-specific linear time trends, our identifying assumption is that there are no omitted variables that correlate with both HYV adoption and child mortality, that vary *nonlinearly* over time and within districts, and that are not accounted for by the mother, child and weather characteristics

[4] Note that the state-by-year fixed effects $\zeta_{sy}$ make the year fixed effects $\eta_y$ redundant. We include them above for expositional clarity.

that we include as observable controls. So, if a policy such as a road-building program were to be implemented that facilitated both access to health care and the availability of new crop varieties in a district, this would be a threat to identification, and our identifying assumption is that unobserved policies of this sort tend to expand at a constant rate over time that can vary across districts. In our specification with state-by-year fixed effects, our identifying assumption is that there are no omitted variables that vary across districts in the same state and in the same year that correlate with both HYV adoption and child mortality, and that are not accounted for by the mother, child and weather characteristics that we include as observable controls. To continue the example from above, our identifying assumption would be that the road program could be expanded at an arbitrarily nonlinear rate, but that this nonlinearity would be uniform across districts of the same state in a given year.

Finally, we add a vector of controls, $x'_{isdy}$, to our baseline specification that includes birth order, a dummy for whether the child born is female, a dummy for whether the child born is a multiple birth, a dummy for DHS round, mother's age in survey, mother's age in survey squared, a dummy for urban, a dummy for the mother's religion, a dummy for the mother's caste, rainfall, and temperature. The controls for rainfall and temperature are added to isolate the impacts of exposure to the Green Revolution from the broader impacts of the weather during the child's year of birth.

We also carry out several robustness exercises to further corroborate our baseline results. First, we replace the district fixed effects with more stringent mother fixed effects. These restrict identification to comparisons of children born to the same mother. The inclusion of this alternative fixed effect has little impact on the baseline results. Second, in addition to the district fixed effects we also include district time trends. Again, the results are of the same sign and magnitude as our baseline estimates, and remain significant at the 5 percent level. Third, we switch our measure of HYV adoption from being based on data in the VDSA dataset to being based on data in the India Agricultural and Climate Dataset (IACD). The sign and significance of our baseline results are similar when we switch the measure. Fourth, we cluster the standard errors by state in the DHS, or survey cluster in the DHS, instead of district. Again the results remain unchanged.

It is important to note here that our paper does not include a structural model that describes the mechanism(s) for our baseline results. Therefore, we interpret our main result as a "reduced form" relationship between HYV adoption and infant mortality. We explore mechanisms later in the paper by examining heterogeneity in responses to HYV adoption, as well as other outcomes that respond to it.

# 5 Results

## 5.1 Main Results

In Table 3 we show the results from estimating our baseline regression in equations (1) and (2). The table shows the impact of HYV adoption on infant–within 12 months of birth–mortality. The results show a substantial and significant reduction in infant mortality from increased HYV adoption. The first two columns include state-specific linear time trends and the last two columns include state by year fixed effects. As we move from the first to the second column or from the third to the fourth column, we find that including controls for rainfall, temperature, the child's attributes, mother's characteristics and a dummy for DHS survey round makes almost no difference to the size and precision of the impact of HYV adoption on infant mortality. This means that it is unlikely that omitted variables correlated with HYV adoption are driving our results (Altonji, Elder, and Taber, 2005).

Interpreting the magnitude of the coefficient on HYV adoption in column 2 of Table 3, we find that a one standard deviation increase in HYV adoption leads to a 0.50 percentage point decrease in infant mortality, or approximately 5.3% of the mean.[5] Our magnitude is comparable to the magnitudes of other determinants of infant and child mortality found in the literature. These include the elasticity of rural infant mortality with respect to aggregate income of -0.33 in India (Bhalotra, 2010), the long-run income elasticity of infant and child mortality with respect to per capita income of between 0.2 and 0.4 in developing countries (Pritchett and Summers, 1996), the 3.27 percent reduction in American infant mortality due to a decrease in the use of bituminous coal for heating (Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016) and the 0.51 percent reduction in American infant mortality from an increase in the unemployment rate (Dehejia, Lleras-Muney, et al., 2004).

It is important to note here that in Appendix Table A1 we show robustness of our baseline results to a range of clustering assumptions: administrative region as recorded

[5]To arrive at this, we multiply the standard deviation of HYV adoption from Table 3 (0.21) by the coefficient (-0.024) in column 2 of Table 3, and then multiply the resulting number by 100 to convert from deaths per birth to percentage points. The confidence interval for the coefficient estimate in column 2 of Table 3 is (-0.038, -0.010).

in the DHS, state, or DHS survey cluster. Indeed, as Appendix Table A1 shows, standard errors are more or less indistinguishable using any of the three alternatives.

### 5.2 Results from heterogeneity analysis

In Table 4 we explore heterogeneity in the effect of HYV adoption on infant mortality. The first four columns of the top panel include the interaction of HYV adoption with child gender. We find that HYV adoption is more effective in reducing the infant mortality of boys relative to girls. Specifically, in column 2 of the top panel the impact of HYV adoption on infant mortality for girls is only about half of that for boys. There are two possible explanations for such a result. First, since male fetuses are more fragile than their female counterparts (Gualtieri and Hicks, 1985; Kraemer, 2000) it is likely that the biological improvements caused by HYV adoption are greater for boys than for girls. That is: because boys start from a lower health endowment, the marginal return to any additional investment may be greater for them. It could also be the case that the greater reduction in infant mortality for boys is due to gender-biased parental investments in early-life health. If parents use the additional income generated from HYV adoption to invest disproportionately in the early-life health of boys then this could explain the heterogeneous effect of HYV adoption across gender.

Columns 5 to 8 of the top panel include the interaction of HYV adoption with a dummy for the child being born to a lower-caste mother. The coefficient estimates on the interaction show that children from lower-caste mothers benefit more from HYV adoption. The results are consistent with poorer (i.e. lower-caste) mothers lacking the financial resources for undertaking investments in early-life health. They also reflect the importance of caste networks in facilitating access to health facilities (Munshi and Rosenzweig, 2009).

The last four columns of the top panel and the first four columns of the bottom panel report results for heterogeneity by two important characteristics of mothers in our sample–age and education. The results show that HYV adoption leads to a smaller decrease in infant mortality for later-married and more educated mothers. Conversely, earlier-married and less educated mothers benefit more from HYV adoption. Such a result suggests that it is mothers whose observable characteristics correlate negatively with child survival who gain more from HYV adoption.

The last four columns of the bottom panel show that there is a greater reduction in infant mortality amongst rural children, relative to urban ones. Specifically, column 10 of the bottom panel shows that the impact of HYV adoption on infant mortality is larger for rural children relative to urban children. Such a result is not surprising as HYV are an agricultural innovation that mainly affected incomes of rural households.[6]

Most of the productivity gains from the adoption of HYV in India have been concentrated in either rice or wheat for two reasons. First, the HYV for these crops are more effective in raising productivity relative to other crops (Evenson and Gollin, 2003b, p. 461). As mentioned earlier, this was because scientists had developed a critical mass of knowledge about these two crops which they had not developed for other crops (Evenson and Gollin, 2003b). Second, wheat and rice are the most extensively cultivated crops in the country. In Table 5 we test for crop-specific heterogeneity in the impact of HYV adoption. We find a negative effect of HYV adoption on infant mortality for both wheat and rice, though the latter is only significant with state-specific trends, and not with state-by-year fixed effects. We also find similar effects for sorghum and pearl millet. There is no impact for maize and finger millet.

## 6 Mechanisms

Our analysis in the previous section has shown that HYV adoption reduces infant mortality across districts in India. We also documented heterogeneity in the effect of infant mortality across a range of dimensions that include the gender of the child, the caste, age and education of the mother, and the locality of the household. While limitations of the available data restrict us from uncovering all possible mechanisms that connect HYV adoption to infant mortality, we consider two important mechanisms in some detail: investments in early life health, and selection of mothers into childbearing. We focus on these mechanisms as data on more fundamental mechanisms such as income and food consumption is not available at the *individual* or local level over time. As Barnwal, Dar, von der Goltz, Fishman, McCord, and Mueller (2017) also acknowledge, since the empirical design here is a difference in difference, any state-wide decline in food prices (which might lead to increased consumption) cannot be captured here as we are comparing areas within states and over time. A firm understanding of the mechanisms behind our

[6]In Appendix Table A2 we show that this is not simply due to differences between children of farmers and other children. Using whether a woman reports that her partner is self-employed in agriculture as a proxy for whether the observation is the child of a farmer, we show the effect is larger for this sub-sample, though the interaction is neither large nor significant.

results and that of Barnwal, Dar, von der Goltz, Fishman, McCord, and Mueller (2017) is crucial, and perhaps an appropriate direction for future research in this area.

### 6.1 Early Childhood Investments

The first of these sets of mechanisms (early childhood investments) is motivated by the idea that parental investment responses have been cited in the literature as a mechanism for other determinants of early-life health (Almond and Mazumder, 2013). We would expect HYV adoption to raise parental investments in child health for two main reasons. First, an increase in agricultural incomes associated with HYV adoption could cause parental investments in health during the prenatal and neonatal stages. Second, HYV adoption could reduce the opportunity cost of maternal time, thereby causing mothers to engage in seeking health-care services (Bhalotra, 2010).

In Table 6 we find no obvious evidence of HYV adoption affecting investments in child health.[7] The top two panels of Table 6 examine the impact of HYV adoption on investments (vaccinations) undertaken between 12 to 23 months after birth. For most investments we find no significance for the impacts. The only exceptions are the 'Polio 1' and 'DPT 1' vaccinations, as well as the "any vaccination" indicator. However, all the coefficients (regardless of significance) are negative in sign, which is surprising as we would expect that with economic progress and increases in incomes, such investments should see positive take up. While a few economic reasons could explain such a finding (for example, increased opportunity cost of parental time or agricultural growth crowding out public goods in healthcare), we wish to be upfront about data limitations here. The vaccination and health investment data is only available for few children born in last 5 years from the survey, which limits the coverage to about one decade only since both DHS rounds used here were conducted within six years in the 1990s. Most importantly, the period for this sub-sample of data comes quite late when HYV adoption had already reached saturation for most of districts (especially in the case of wheat). Further, because there are several of these correlated vaccine outcomes, there is a risk that we have rejected the null hypothesis of zero by chance. As a result, while we are unable to take a deep dive into why this correlation is negative in this instance, what it implies for our results is that *despite* the potentially negative impact on early childhood investments, the Green Revolution led to a decline in infant mortality.

[7] The child health investment variables used in Table 6 are described in Table 2.

The third panel of Table 6 shows how pre-natal and at-birth investments respond to HYV adoption. Since such investment decisions are made before the child's birth, they reflect the impact of HYV adoption on 'access' to health care services, rather than 'compensatory' investments by parents once child quality is revealed (Bharadwaj, Eberhard, and Neilson, 2017). We find no evidence that HYV adoption is related to pre-natal and at-birth investments. In sum, then, there is not much evidence of greater parental investments explaining the effects that we find.

Finally, in the bottom panel of Table 6 we examine the impact of HYV adoption on early childhood health outcomes beyond the infancy period. We do this to learn more about the health profile of children who survive the infancy period. If HYV adoption helped only the weakest children survive, then we would expect those children whose survival depended upon HYV adoption to have worse health outcomes. We do not find much evidence for HYV adoption being negatively associated with health outcomes of surviving children such as height, weight, birth size, recent fever and recent diarrhea, but we do find a significantly negative effect for recent coughs.

### 6.2 Selection

HYV adoption can also affect infant mortality by influencing the profile of mothers who give birth. For instance, Dehejia, Lleras-Muney, et al. (2004) and Bhalotra (2010) find that recessions cause high-risk mothers to delay their fertility decisions. In our case, if parents with both education and experience decide to have more children in response to HYV adoption, then such self-selection of parents with characteristics that predict child survival into childbearing could explain why HYV adoption reduces infant mortality. We, therefore, test for whether selective fertility based on either parental or child characteristics can explain the effect of HYV adoption on infant mortality. To do so, we estimate equation (1) and (2) with predetermined parental and child characteristics as the outcome variables. Our test for selection is motivated by Buckles and Hungerman (2013). In Table 7 we find that HYV adoption has little "effect" on predetermined characteristics of mothers or children. In one specification, there is a positive coefficient for the mother's education that is significant at the 10% level. It also appears that children are more likely to be female in districts where HYV adoption has expanded: this may reflect greater survival until birth, though our main results in Table 3 do control for child gender.

## 7 Robustness

In this section we perform a series of empirical exercises to show the robustness of our main results. Wherever possible, we have organized the results from the robustness exercises in the same way as our baseline results in Table 3, meaning that, for each variant of the baseline specification, there are two columns: one for the parsimonious model without controls and the other for the model with controls.

First, in Table 8, we replace the district fixed effects with mother fixed effects. Hence, we are comparing children born to the same mother but at different times of HYV penetration. Columns 1-4 of Table 8 show results consistent with our previous results on the impact of HYV penetration on infant mortality across siblings. Second, in Table 9, we replace the state-specific time trends or state-by-year fixed effects from our baseline specification with district time trends to account for any unobserved trending variables that could vary by district-specific birth cohort. Despite the inclusion of the district time trends the results have the same sign and magnitude as our baseline estimates, and remain significant at the 5 percent level.

In addition to the above robustness exercises, we perform a series of additional robustness tests in the Appendix. These tables show that our results are robust to using child mortality as an outcome, using a non-linear specification, exclusion of districts with extreme values of HYV adoption, clustering at different levels, alternative data from the IACD, using leads and lags of HYV adoption, among various other checks. We urge the interested reader to see the discussion of these results in the Appendix.

## 8 Conclusion

This paper shows that the adoption of HYV reduces infant mortality in India during the period 1966 to 1998. While there exist studies that have examined the microeconomic effects of technology adoption and identified sources of poor health outcomes in developing countries, our paper contributes to such a literature in several ways. First, by connecting HYV adoption with infant mortality, we focus on the role played by technological change in influencing health outcomes in developing countries. Second, by restricting our study to India, we are able to compare areas that have similar political and administrative arrangements, which is not the case in cross-country studies. Third, we use heterogeneous impacts of HYV adoption to identify those groups that benefit most from HYV adoption in terms of reduced mortality. These include children born to low-caste mothers, girls, and children in rural areas. Fourth, we show that parental investments in either early life health or the health of children who survive beyond infancy are not strongly correlated with HYV adoption.

## References


Almond, D., and B. Mazumder (2013): "Fetal origins and parental responses," *Annual Review of Economics*, 5(1), 37–56.

Altonji, J. G., T. E. Elder, and C. R. Taber (2005): "Selection on observed and unobserved variables: Assessing the Effectiveness of Catholic Schools," *Journal of Political Economy*, 113(1), 151–184.

Barker, R., R. W. Herdt, and B. Rose (1985): *The rice economy of Asia, Volume 2*. International Rice Research Institute.

Barnwal, P., A. Dar, J. von der Goltz, R. Fishman, G. C. McCord, and N. Mueller (2017): "Modern Crop Variety Diffusion and Infant Mortality in the Developing World, 1961-2000," .

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J. S. Shapiro (2016): "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century," *Journal of Political Economy*, 124(1), 105–159.

Bhalotra, S. (2010): "Fatal fluctuations? Cyclicality in infant mortality in India," *Journal of Development Economics*, 93(1), 7–19.

Bharadwaj, P., J. Eberhard, and C. Neilson (2017): "Health at birth, parental investments and academic outcomes," *Journal of Labor Economics*, 36(2), 349–394.

Borlaug, N. E. (2002): *The green revolution revisited and the road ahead*. Nobelprize. org Stockholm, Sweden.

Brainerd, E., and N. Menon (2014): "Seasonal effects of water quality: The hidden costs of the Green Revolution to infant and child health in India," *Journal of Development Economics*, 107, 49–64.

Buckles, K. S., and D. M. Hungerman (2013): "Season of birth and later outcomes: Old questions, new answers," *Review of Economics and Statistics*, 95(3), 711–724.

Bustos, P., B. Caprettini, J. Ponticelli, et al. (2016): "Agricultural Productivity and Structural Transformation: Evidence from Brazil," *American Economic Review*, 106(6), 1320–1365.

Currie, J., and T. Vogl (2013): “Early-life health and adult circumstance in developing countries,” *Annual Review of Economics*, 5(1), 1–36.

Cutler, D. M., F. Knaul, R. Lozano, O. Méndez, and B. Zurita (2002): “Financial crisis, health outcomes and ageing: Mexico in the 1980s and 1990s,” *Journal of Public Economics*, 84(2), 279–303.

D’Agostino, A. L. (2017): “Technical Change and Gender Wage Inequality: Long-Run Effects of India’s Green Revolution,” *UC Riverside Working Paper*.

Dalrymple, D. G. (2008): “International agricultural research as a global public good: concepts, the CGIAR experience and policy issues,” *Journal of International Development*, 20(3), 347–379.

Dehejia, R. H., A. Lleras-Muney, et al. (2004): “Booms, busts, and babies’ health,” *The Quarterly Journal of Economics*, 119(3), 1091–1130.

Dexter, E. R., S. E. LeVine, and P. M. Velasco (1998): “Maternal schooling and health-related language and literacy skills in rural Mexico,” *Comparative education review*, 42(2), 139–162.

Estudillo, J. P., and K. Otsuka (2013): *Lessons from the Asian Green Revolution in Rice*pp. 17–42. Springer Netherlands.

Evenson, R. E., and D. Gollin (2003a): “Assessing the impact of the Green Revolution, 1960 to 2000,” *Science*, 300(5620), 758–762.

——— (2003b): *Crop variety improvement and its effect on productivity: The impact of international agricultural research*. Cabi Publishing.

Fan, S., L. Zhang, and X. Zhang (2000): “Growth, Inequality and Poverty in Rural China: The Role of Public Investments,” *Environment and Production Technology Division Discussion Paper*, (66).

Foster, A. D., and M. R. Rosenzweig (1995): “Learning by doing and learning from others: Human capital and technical change in agriculture,” *Journal of Political Economy*, 103(6), 1176–1209.

——— (1996): “Technical change and human-capital returns and investments: Evidence from the Green Tevolution,” *The American Economic Review*, pp. 931–953.

Gollin, D., C. W. Hansen, and A. M. Wingender (2016): "Two Blades of Grass: The Impact of the Green Revolution," *Centre for Economic Policy Research Discussion Paper DP11611*.

Gualtieri, T., and R. E. Hicks (1985): "An immunoreactive theory of selective male affliction," *Behavioral and Brain Sciences*, 8(03), 427–441.

Hornbeck, R., and P. Keskin (2014): "The Historically Evolving Impact of the Ogallala Aquifer: Agricultural Adaption to Groundwater and Climate," *American Economic Journal: Applied Economics*, 6(1), 190–219.

Kraemer, S. (2000): "The fragile male," *British Medical Journal*, 321(7276), 1609.

LeVine, R. A., S. LeVine, B. Schnell-Anzola, M. L. Rowe, and E. Dexter (2011): *Literacy and mothering: How women's schooling changes the lives of the world's children*. Oxford University Press.

LeVine, R. A., S. E. LeVine, M. L. Rowe, and B. Schnell-Anzola (2004): "Maternal literacy and health behavior: a Nepalese case study," *Social Science & Medicine*, 58(4), 863–877.

LeVine, R. A., and M. L. Rowe (2009): "Maternal literacy and child health in less-developed countries: evidence, processes, and limitations," *Journal of Developmental & Behavioral Pediatrics*, 30(4), 340–349.

Maluccio, J. A., et al. (2005): *Coping with the 'coffee crisis' in Central America: The Role of the Nicaraguan Red de Protección Social*. IFPRI Washington, DC.

Matsuura, K., and C. J. Willmott (2009): "Terrestrial precipitation: 1900-2010 gridded monthly time series," .

Meinzen-Dick, R., M. Adato, L. Haddad, and P. Hazell (2003): *Impacts of agricultural research on poverty: findings of an integrated economic and social analysis*. IFPRI Washington, DC.

Munshi, K. (2004): "Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution," *Journal of Development Economics*, 73(1), 185–213.

Munshi, K., and M. Rosenzweig (2009): "Why is mobility in India so low? Social insurance, inequality, and growth," *NBER Working Paper w14850*.

Nunn, N., and N. Qian (2011): "The potato's contribution to population and urbanization: Evidence from an historical experiment," *The Quarterly Journal of Economics*, 126(2), 593–650.

Paxson, C., and N. Schady (2005): "Child health and economic crisis in Peru," *The World Bank Economic Review*, 19(2), 203–223.

Pingali, P. L. (2012): "Green revolution: impacts, limits, and the path ahead," *Proceedings of the National Academy of Sciences*, 109(31), 12302–12308.

Pingali, P. L., P. Moya, and L. E. Velasco (1990): "The post-green revolution blues in Asian rice production," Discussion paper, Manila, Philippines : Social Science Division, International Rice Research Institute.

Pongou, R., J. A. Salomon, and M. Ezzati (2006): "Health impacts of macroeconomic crises and policies: determinants of variation in childhood malnutrition trends in Cameroon," *International Journal of Epidemiology*, 35(3), 648–656.

Pritchett, L., and L. H. Summers (1996): "Wealthier is Healthier," *Journal of Human Resources*, 31(4), 841–868.

Schnell-Anzola, B., M. L. Rowe, and R. A. LeVine (2005): "Literacy as a pathway between schooling and health-related communication skills: a study of Venezuelan mothers," *International Journal of Educational Development*, 25(1), 19–37.

Smith-Greenaway, E. (2017): "Community Context and Child Health: A Human Capital Perspective," *Journal of Health and Social Behavior*, 58(3), 307–321.

Table 1. Summary Statistics

| | (1) Mean | (2) s.d. | (3) Min | (4) Max | (5) N |
|---|---|---|---|---|---|
| *Mother Characteristics* | | | | | |
| Current Age - Respondent | 35.2 | 7.78 | 13 | 49 | 331,838 |
| Education In Single Years | 2.10 | 3.70 | 0 | 22 | 331,352 |
| Age At First Marriage | 16.1 | 2.78 | 8 | 48 | 331,838 |
| Can Read And Write | 0.20 | 0.40 | 0 | 1 | 299,708 |
| Completed Primary | 0.30 | 0.46 | 0 | 1 | 331,838 |
| Completed Secondary | 0.16 | 0.37 | 0 | 1 | 331,838 |
| Urban | 0.25 | 0.43 | 0 | 1 | 331,838 |
| Low Caste | 0.32 | 0.47 | 0 | 1 | 330,627 |
| Tribal | 0.099 | 0.30 | 0 | 1 | 330,627 |
| Muslim : Muslim and Hindu Sample Only | 0.12 | 0.32 | 0 | 1 | 313,226 |
| *Child Characteristics* | | | | | |
| Birth Order Number | 2.83 | 1.84 | 1 | 16 | 331,838 |
| Year Of Birth | 1,983 | 7.30 | 1,966 | 1,999 | 331,838 |
| Child Multiple | 0.012 | 0.11 | 0 | 1 | 331,838 |
| Child Female | 0.48 | 0.50 | 0 | 1 | 331,838 |
| Child Died As Infant | 0.098 | 0.30 | 0 | 1 | 331,838 |
| *Green Revolution* | | | | | |
| Total HYV Area / Total Cultivated Area | 0.29 | 0.21 | 0 | 0.96 | 331,838 |
| *Weather Controls* | | | | | |
| Rainfall (in millimetres) | 84.7 | 45.9 | 2.03 | 465 | 331,838 |
| Temperature (in degree celsius) | 25.6 | 1.65 | 4.94 | 29.8 | 331,838 |

Notes: The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. The summary statistics are based on a panel from 1966 to 1999.

Table 2. Description of Variables

| Variable | Description |
|---|---|
| Round | DHS round (i.e. round 23 or 42) |
| Unique Mother ID | Unique ID of the respondent mother in the DHS |
| District ID VDSA | Unique ID of districts in the VDSA |
| Current Age - Respondent | Age of the respondent mother at the time enumeration |
| Education In Single Years | Years of education of the respondent mother |
| Age At First Marriage | Age of the respondent mother at the time of her first marriage |
| Can Read And Write | Whether the respondent mother can read and write |
| Completed Primary | Whether the respondent mother has completed primary education |
| Completed Secondary | Whether the respondent mother has completed secondary education |
| Urban | Whether the household to which the respondent mother belongs is in an urban area |
| Low Caste | Whether the respondent mother comes from “scheduled caste” or “other backward caste” |
| Tribal | Whether the respondent mother comes from a “scheduled tribe” |
| Muslim | Whether the respondent mother is muslim |
| Birth Order Number | Birth order of the child |
| Year Of Birth | Year in which the child is born |
| Child Multiple | Whether the child was part of a twin birth |
| Child Female | Whether the child is female |
| Child Died As Infant | Whether the child died in his/her infancy |
| Child Died As Child | Whether the child died in his/her childhood |
| Total HYV Area / Total Cultivated Area | Proportion of total cultivated area in a district that is planted to high yielding varieties in a given year |
| Rainfall (in millimetres) | Average annual rainfall (in millimetres) at the district level in a given year |
| Temperature (in degree celsius) | Average annual temperature (in degree celsius) at the district level in a given year |
| Pre-natal doctor | Whether the respondent mother received pre-natal doctor care |
| Doctor at birth | Whether the respondent mother was assisted by a doctor at the birth of the child |
| Breastfeeding duration | Number of months the respondent mother breastfed the child |
| Prenatal visits | Number of visits the respondent mother made to the health clinic during pregnancy |
| Iron tablet | Whether the respondent mother received an iron tablet |
| Birth size | Respondent mother's subjective assessment of her child's size at birth |
| Recent diarrhea | Whether the respondent mother has had diarrhea recently |
| Recent fever | Whether the respondent mother has had a fever recently |
| Recent cough | Whether the respondent mother has had a cough recently |
| Weight | Weight of the child in kilograms |
| Height | Height of the child in centimeters |
| Tetanus | The number of tetanus injections the respondent mother received before the child's birth |
| BCG | Whether the child received the BCG (Bacille Calmette-Guérin) vaccine shortly after birth |
| Polio 1 | Whether the child received the Polio 1 vaccine shortly after birth |
| Polio 2 | Whether the child received the Polio 2 vaccine shortly after birth |
| Polio 3 | Whether the child received the Polio 3 vaccine shortly after birth |
| DPT 1 | Whether the child received the DPT (Diphtheria-Pertussis-Tetanus) 1 vaccine shortly after birth |
| DPT 2 | Whether the child received the DPT (Diphtheria-Pertussis-Tetanus) 2 vaccine shortly after birth |
| DPT 3 | Whether the child received the DPT (Diphtheria-Pertussis-Tetanus) 3 vaccine shortly after birth |
| Measles | Whether the child received the Measles vaccine shortly after birth |
| Any | Whether the child received any of the relevant vaccines shortly after birth |

Notes: The data sources from which the variables come from are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99.

Table 3. Impact of HYV cultivation on infant mortality

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Child Died As Infant | | | |
| Total HYV Area / Total Cultivated Area | -0.025*** | -0.024*** | -0.027*** | -0.027*** |
| | (0.007) | (0.007) | (0.009) | (0.009) |
| Observations | 331,838 | 330,577 | 331,838 | 330,577 |
| Mean outcome | 0.0981 | 0.0979 | 0.0981 | 0.0979 |
| R-squared | 0.016 | 0.038 | 0.018 | 0.040 |
| District FE | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | Yes | N/A | N/A |
| State YOB trends | Yes | Yes | No | No |
| State YOB FE | No | No | Yes | Yes |
| Controls | No | Yes | No | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1-2 estimate equation (3) whereas columns 3-4 estimate equation (4). Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.

Table 4. Heterogeneous effects of HYV cultivation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Child Died As Infant | | | | | | | | | | | |
| Total HYV Area / Total Cultivated Area | -0.032*** | -0.031*** | -0.034*** | -0.034*** | -0.019** | -0.017** | -0.022** | -0.019** | -0.061*** | -0.091*** | -0.058*** | -0.088*** |
| | (0.008) | (0.008) | (0.010) | (0.009) | (0.008) | (0.007) | (0.009) | (0.009) | (0.020) | (0.020) | (0.021) | (0.021) |
| Interaction | 0.014*** | 0.015*** | 0.015*** | 0.015*** | -0.016** | -0.020*** | -0.016** | -0.020*** | 0.002** | 0.004*** | 0.002* | 0.004*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.007) | (0.007) | (0.007) | (0.007) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 331,838 | 330,577 | 331,838 | 330,577 | 330,627 | 330,577 | 330,627 | 330,577 | 331,838 | 330,577 | 331,838 | 330,577 |
| Mean outcome | 0.0981 | 0.0979 | 0.0981 | 0.0979 | 0.0981 | 0.0979 | 0.0981 | 0.0979 | 0.0981 | 0.0979 | 0.0981 | 0.0979 |
| R-squared | 0.016 | 0.038 | 0.018 | 0.040 | 0.017 | 0.038 | 0.018 | 0.040 | 0.017 | 0.039 | 0.019 | 0.040 |
| P-value for interaction | 0.0275 | 0.0298 | 0.0408 | 0.0333 | 0.0001 | 0.0000 | 0.0002 | 0.0001 | 0.0020 | 0.0000 | 0.0068 | 0.0001 |
| Interaction variable | Child female | | Child female | | Mother low caste | | Mother low caste | | Mother age at marriage | | Mother age at marriage | |
| | Child Died As Infant | | | | | | | | | | | |
| Total HYV Area / Total Cultivated Area | -0.032*** | -0.031*** | -0.033*** | -0.034*** | -0.027*** | -0.025*** | -0.029*** | -0.028*** | -0.030*** | -0.030*** | -0.031*** | -0.032*** |
| | (0.008) | (0.007) | (0.009) | (0.009) | (0.008) | (0.008) | (0.010) | (0.009) | (0.008) | (0.007) | (0.009) | (0.009) |
| Interaction | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.009 | 0.003 | 0.011 | 0.004 | 0.022*** | 0.024*** | 0.021*** | 0.023*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.011) | (0.010) | (0.011) | (0.010) | (0.008) | (0.008) | (0.008) | (0.008) |
| Observations | 331,352 | 330,091 | 331,352 | 330,091 | 313,226 | 312,027 | 313,226 | 312,027 | 331,838 | 330,577 | 331,838 | 330,577 |
| Mean outcome | 0.0981 | 0.0979 | 0.0981 | 0.0979 | 0.100 | 0.100 | 0.100 | 0.100 | 0.0981 | 0.0979 | 0.0981 | 0.0979 |
| R-squared | 0.019 | 0.039 | 0.021 | 0.041 | 0.016 | 0.038 | 0.018 | 0.040 | 0.018 | 0.038 | 0.019 | 0.040 |
| P-value for interaction | 0.0002 | 0.0001 | 0.0012 | 0.0006 | 0.1370 | 0.0367 | 0.1520 | 0.0387 | 0.4100 | 0.5180 | 0.3430 | 0.3750 |
| Interaction variable | Mother education | | Mother education | | Mother Muslim | | Mother Muslim | | Urban | | Urban | |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | Yes | N/A | N/A | Yes | Yes | N/A | N/A | Yes | Yes | N/A | N/A |
| State YOB trends | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes | No | No |
| State YOB FE | No | No | Yes | Yes | No | No | Yes | Yes | No | No | Yes | Yes |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1-2, 5-6 and 9-10 estimate a variant of equation (3) whereas columns 3-4, 7-8 and 11-12 estimate a variant of equation (4). The variant being the addition of an interaction term where the measure for HYV adoption is interacted with various characteristics of the mother/child. Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.

Table 5. Effects of specific crops

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Child Died As Infant | | | | | | | | | | | |
| Crop HYV Area / Total Cultivated Area | -0.020* | -0.014 | -0.029* | -0.044** | -0.051** | -0.044** | -0.048** | -0.063** | 0.002 | 0.020 | 0.009 | 0.002 |
| | (0.011) | (0.012) | (0.016) | (0.021) | (0.022) | (0.022) | (0.023) | (0.024) | (0.038) | (0.039) | (0.033) | (0.034) |
| Observations | 330,837 | 330,837 | 330,837 | 330,837 | 331,025 | 331,025 | 329,779 | 329,779 | 329,079 | 329,079 | 307,134 | 307,134 |
| Mean outcome | 0.0979 | 0.0979 | 0.0979 | 0.0979 | 0.0979 | 0.0979 | 0.0978 | 0.0978 | 0.0979 | 0.0979 | 0.0985 | 0.0985 |
| R-squared | 0.038 | 0.040 | 0.038 | 0.040 | 0.038 | 0.040 | 0.038 | 0.040 | 0.038 | 0.040 | 0.039 | 0.040 |
| Crop | Rice | | Wheat | | Sorghum | | Pearl Millet | | Maize | | Finger Millet | |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A |
| State YOB trends | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| State YOB FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1, 3, 5, 7, 9 and 11 estimate a variant of equation (3) whereas columns 2, 4, 6, 8, 10 and 12 estimate a variant of equation (4). The variant being the total HYV adoption measure being replaced by various crop-specific HYV adoption measures. Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.

Table 6. Impact of HYV cultivation on child investments and outcomes

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Vaccines received A:* | Tetanus | | BCG | | DPT 1 | | Polio 1 | | DPT 2 | | | |
| Total HYV Area / Total Cultivated Area | -0.052 | -0.035 | -0.061 | -0.011 | -0.122*** | -0.096** | -0.144*** | -0.118** | -0.075 | -0.030 | | |
| | (0.107) | (0.124) | (0.043) | (0.046) | (0.043) | (0.048) | (0.047) | (0.051) | (0.048) | (0.051) | | |
| Observations | 35,136 | 35,136 | 34,648 | 34,648 | 34,546 | 34,546 | 34,695 | 34,695 | 34,521 | 34,521 | | |
| Mean outcome | 1.5094 | 1.5094 | 0.6065 | 0.6065 | 0.6132 | 0.6132 | 0.6510 | 0.6510 | 0.5421 | 0.5421 | | |
| R-squared | 0.278 | 0.279 | 0.243 | 0.249 | 0.244 | 0.253 | 0.243 | 0.252 | 0.269 | 0.283 | | |
| *Vaccines received B:* | Polio 2 | | DPT 3 | | Polio 3 | | Measles | | Any | | | |
| Total HYV Area / Total Cultivated Area | -0.127** | -0.077 | -0.027 | -0.003 | -0.090* | -0.060 | -0.077 | -0.035 | -0.159*** | -0.092* | | |
| | (0.052) | (0.051) | (0.049) | (0.055) | (0.052) | (0.053) | (0.049) | (0.044) | (0.051) | (0.054) | | |
| Observations | 34,671 | 34,671 | 34,521 | 34,521 | 34,671 | 34,671 | 34,093 | 34,093 | 26,328 | 26,328 | | |
| Mean outcome | 0.5803 | 0.5803 | 0.4561 | 0.4561 | 0.4766 | 0.4766 | 0.3793 | 0.3793 | 0.5991 | 0.5991 | | |
| R-squared | 0.262 | 0.275 | 0.280 | 0.296 | 0.253 | 0.266 | 0.275 | 0.295 | 0.235 | 0.242 | | |
| *Care received:* | Pre-natal doctor | | Doctor at birth | | Breastfeeding duration | | Prenatal visits | | Iron tablet | | | |
| Total HYV Area / Total Cultivated Area | 0.041 | 0.026 | 0.003 | -0.009 | -1.463 | 0.257 | 0.400* | 0.355 | 0.040 | 0.032 | | |
| | (0.042) | (0.050) | (0.042) | (0.054) | (1.444) | (1.258) | (0.238) | (0.288) | (0.044) | (0.054) | | |
| Observations | 35,380 | 35,380 | 35,316 | 35,316 | 35,109 | 35,109 | 35,468 | 35,468 | 35,317 | 35,317 | | |
| Mean outcome | 0.4068 | 0.4068 | 0.2427 | 0.2427 | 14.1267 | 14.1267 | 2.6952 | 2.6952 | 0.5767 | 0.5767 | | |
| R-squared | 0.297 | 0.298 | 0.230 | 0.232 | 0.389 | 0.402 | 0.324 | 0.326 | 0.247 | 0.249 | | |
| *Health outcome:* | Birth size | | Recent diarrhea | | Recent fever | | Recent cough | | Weight | | Height | |
| Total HYV Area / Total Cultivated Area | 0.068 | 0.132 | 0.019 | 0.013 | -0.011 | -0.002 | -0.081** | -0.071* | -0.455 | -0.205 | -1.737 | -1.018 |
| | (0.073) | (0.084) | (0.035) | (0.042) | (0.040) | (0.041) | (0.038) | (0.041) | (0.350) | (0.410) | (1.552) | (1.861) |
| Observations | 35,116 | 35,116 | 32,614 | 32,614 | 32,617 | 32,617 | 32,620 | 32,620 | 28,400 | 28,400 | 23,192 | 23,192 |
| Mean outcome | 3.1120 | 3.1120 | 0.1335 | 0.1335 | 0.2107 | 0.2107 | 0.2152 | 0.2152 | 8.8138 | 8.8138 | 75.1657 | 75.1657 |
| R-squared | 0.055 | 0.057 | 0.063 | 0.069 | 0.058 | 0.063 | 0.079 | 0.084 | 0.526 | 0.531 | 0.489 | 0.492 |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A |
| State YOB trends | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| State YOB FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1988 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1, 3, 5, 7, 9 and 11 estimate a variant of equation (3) whereas columns 2, 4, 6, 8, 10 and 12 estimate a variant of equation (4). The variant being that infant mortality is replaced by various measures of child health investment as the depdent variable. Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.

Table 7. Selective fertility and survival to birth

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| *Mother characteristics A* | Low Caste | | Tribal | | Age in survey | | Age at first marriage | | Education | |
| Total HYV Area / Total Cultivated Area | -0.020 | -0.025 | 0.000 | -0.003 | -0.145 | -0.265 | 0.129 | 0.143 | 0.182 | 0.241* |
| | (0.016) | (0.019) | (0.007) | (0.010) | (0.232) | (0.279) | (0.093) | (0.115) | (0.120) | (0.145) |
| Observations | 330,627 | 330,627 | 330,627 | 330,627 | 331,838 | 331,838 | 331,838 | 331,838 | 331,352 | 331,352 |
| Mean outcome | 0.3230 | 0.3230 | 0.0993 | 0.0993 | 35.1920 | 35.1920 | 16.1061 | 16.1061 | 2.1031 | 2.1031 |
| R-squared | 0.113 | 0.115 | 0.249 | 0.250 | 0.536 | 0.537 | 0.183 | 0.184 | 0.123 | 0.125 |
| *Mother characteristics B* | Muslim | | Completed primary | | Completed secondary | | Urban | | Literate | |
| Total HYV Area / Total Cultivated Area | 0.009 | 0.014 | 0.018 | 0.022 | 0.015 | 0.022 | 0.008 | 0.005 | 0.019 | 0.022 |
| | (0.011) | (0.013) | (0.016) | (0.020) | (0.012) | (0.013) | (0.013) | (0.017) | (0.016) | (0.019) |
| Observations | 313,226 | 313,226 | 331,838 | 331,838 | 331,838 | 331,838 | 331,838 | 331,838 | 299,708 | 299,708 |
| Mean outcome | 0.1156 | 0.1156 | 0.3040 | 0.3040 | 0.1596 | 0.1596 | 0.2512 | 0.2512 | 0.2035 | 0.2035 |
| R-squared | 0.123 | 0.124 | 0.128 | 0.129 | 0.098 | 0.099 | 0.193 | 0.194 | 0.087 | 0.089 |
| *Child characteristics* | Birth order | | Female | | Multiple | | | | | |
| Total HYV Area / Total Cultivated Area | 0.012 | 0.017 | 0.022** | 0.028** | 0.001 | 0.001 | | | | |
| | (0.068) | (0.086) | (0.010) | (0.013) | (0.004) | (0.004) | | | | |
| Observations | 331,838 | 331,838 | 331,838 | 331,838 | 331,838 | 331,838 | | | | |
| Mean outcome | 2.8319 | 2.8319 | 0.4790 | 0.4790 | 0.0122 | 0.0122 | | | | |
| R-squared | 0.054 | 0.055 | 0.002 | 0.003 | 0.003 | 0.005 | | | | |
| District FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A | Yes | N/A |
| State YOB trends | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
| State YOB FE | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |
| Controls | No | No | No | No | No | No | No | No | No | No |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1, 3, 5, 7 and 9 estimate a variant of equation (3) whereas columns 2, 4, 6, 8 and 10 estimate a variant of equation (4). The variant being that infant mortality is replaced by various characteristics of the mother or child as the dependent variable.

Table 8. Main results with mother fixed effects

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Child Died As Infant | | | |
| Total HYV Area / Total Cultivated Area | -0.021** | -0.021** | -0.015 | -0.020* |
| | (0.009) | (0.009) | (0.011) | (0.011) |
| Observations | 321,217 | 319,972 | 321,217 | 319,972 |
| Mean outcome | 0.0993 | 0.0992 | 0.0993 | 0.0992 |
| R-squared | 0.301 | 0.313 | 0.303 | 0.315 |
| Fixed effects | Mother ID + year of birth | | | |
| State YOB trends | Yes | Yes | No | No |
| State YOB FE | No | No | Yes | Yes |
| Controls | No | Yes | No | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1-2 estimate a variant of equation (3) whereas columns 3-4 estimate a variant of equation (4). The variant being the replacement of district fixed effects with mother fixed effects. Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.

Table 9. Main results with trends for districts

| | (1) | (2) |
|---|---|---|
| | Child Died As Infant | |
| Total HYV Area / Total Cultivated Area | -0.020** | -0.019** |
| | (0.008) | (0.008) |
| Observations | 331,838 | 330,577 |
| Mean outcome | 0.0981 | 0.0979 |
| R-squared | 0.018 | 0.040 |
| District FE | Yes | Yes |
| Birth Year FE | Yes | Yes |
| Controls | No | Yes |

Notes: ***Significant at 1%, **Significant at 5%, *Significant at 10%. Standard errors clustered by district in parentheses, unless otherwise indicated. All regressions are OLS and are based on a panel from 1966 to 1999. The data sources used are the Village Dynamics in South Asia dataset and the Demographic Health Surveys (India) of 1992-93 and 1998-99. Columns 1-2 estimate a variant of equation (3). The variant being the replacement of State YOB trends with District YOB trends. Controls are rainfall, temperature, birth order, female, multiple, DHS round, mother's age in survey, mother's age in survey squared, urban, mother's religion, and mother's caste, unless otherwise indicated.