

Modern Crop Variety Diffusion and Infant Mortality in the Developing World, 1961-2000

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Abstract

The development and diffusion of modern, high-yielding seed varieties (MVs) played a central role in the Green Revolution, but the welfare benefits of this technological revolution remain a topic of substantial debate. We provide novel estimates of the impacts of the spread of MVs on infant mortality, a powerful summary measure of human welfare, across 36 countries in the developing world. Our analysis makes use of geocoded survey data on the births of nearly 600,000 children, coupled with newly constructed, spatially precise proxies of MV adoption. Across our sample, the proportion of cropped area planted to MVs rose from 0% in the 1960s to an average of 21% in 2000. Our estimates suggest that this diffusion of MVs led to around a 3-4 percentage point decrease in infant mortality (from a baseline of 17%), averting around 3-5 million infant deaths per year by 2000. We further show that the impact is significantly higher for male infants. Our results provide new empirical evidence to the debate on the merits of continued investment in improving agricultural technology.

Keywords: Agricultural technology, Modern varieties, Infant mortality.

JEL codes: I15, O13, Q16

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1 Introduction

Modern crop varieties (MVs), developed by dozens of national agriculture programs with the support of the research centers of the Consultative Group for International Agricultural Research, spread globally during the past 70 years in one of the most far-reaching technological revolutions of modern time. While there is little disagreement that the use of MV seeds played a large part in the 20th century's dramatic increase in staple crop production (Evenson and Gollin 2003), much less is known about the direct impacts of MV adoption on household welfare (Masters 2014).

In recent years, the impacts of agricultural productivity gains on human welfare have come under renewed scrutiny. On the one hand, few scholars dispute the benefits of the 'green revolution' - the spread of modern, high-yielding varieties (MVs) of cereal crops and intensive management practices - for food production and caloric intake (Evenson and Gollin, 2003a). On the other hand, several scholars emphasize its negative impacts on the environment, crop and dietary diversity, and argue that strategic re-evaluation of R&D priorities for agriculture is warranted (Murgai et al., 2001; Perfecto and Vandermeer, 2010; McIntyre, 2009; Brainerd and Menon, 2014). These doubts are echoed in the steady decline in funding for cereal crop improvement over the last few decades (Beintema and Stads, 2006; Walker and Alwang, 2015). Some researchers also question whether investing in increased agricultural productivity by smallholder farmers is the most effective strategy for economic development, health improvement, and poverty alleviation in sub-Saharan Africa (Collier and Dercon, 2014; Dercon, 2009; Evenson and Gollin, 2003a; McIntyre, 2009).

For the debate on the overall merit of improved cereal varieties to be empirically informed, it is important to accurately evaluate the benefits of MV diffusion. However, credible estimates of the causal welfare impacts of the spread of varieties in the 20th century remain surprisingly scarce, and are mostly confined to studies in single countries (Fan et al., 2002, 2001) or subnational regions (Pinstrup-Andersen and Jaramillo, 1991). In this paper, we provide such evidence at a precision and scale that has not been attempted to date, using spatially precise household level data on children born between 1959 and 2001 collected in 37 developing countries. The analysis improves upon existing literature in several dimensions, as we discuss below.

To improve the prospects for causal inference, we construct high resolution, sub-national proxies of MV diffusion and couple them to geo-referenced household-level IM indicators from publicly available household survey data. MV proxies are constructed by combining high-resolution global crop maps with country level indicators of MV diffusion. IM data is collected from Demographic and Health Surveys (DHS) in 37 developing countries (Figure 1), and includes more than 600,000 child observations. Our results suggest that the diffusion of MVs contributed to improvements in infant health. We find that one standard deviation (1σ) increase in MV diffusion decreased child's infant mortality risk by about 9% (from 10% to 9.1%). We further look into heterogeneous effect on gender, and our estimates suggest the MV diffusion improves the health of male infants more than female infants. We also document region-wise heterogeneity in the impact of MV diffusion.

The development and diffusion of MVs, along with associated increases in agronomic inputs (e.g. fertilizers, irrigation, and pest control), are thought to have driven the dramatic improvements in

agricultural productivity and calorie production per capita that have taken place in the course of the 20th century in many (but not all) developing countries. There are multiple potential pathways through which increases in yields can improve human health and welfare. Increases in supply can reduce food prices, leading to higher consumption and improved food intake. For farmers who are net food sellers, income may also increase (depending on how far prices decline). At the aggregate economy level, yield increases might also have triggered broader structural transformation in the economy leading to urbanization, higher productivity, a larger tax base and subsequent public health investments (McArthur and Sachs, 2011; McArthur and McCord, 2014). Some researchers have argued that ‘green revolutions’ underpin later stages of economic growth, and cite Africa’s relative lack of a green revolution as a key reason why the region has not yet experienced greater long-term economic success (Diao et al., 2010).

Despite these myriad possible channels of influence, empirical assessments of the historical association between the diffusion of MVs and human welfare on a global scale are severely limited by data availability. Correlations at the country level are both inconclusive (see below) and particularly difficult to interpret because agricultural productivity and a range of welfare indicators trend together as part of the general process of economic development, whose underlying root causes remain debated (although a recent paper by Gollin et al. (2016), uses a novel methodology to disentangle the effects of MVs). Unfortunately, high quality sub-national data on MV diffusion is unavailable at the required spatial and temporal resolution and scale. This makes the causal impacts of past MV diffusion on human health difficult to disentangle.

Our analysis focuses on the effects of MV diffusion, and associated increases in agronomic inputs, on a powerful summary indicator of health and welfare: infant mortality (IM). IM is highly correlated with income across and within countries, as well as over time and is widely used to assess levels of economic development (Baird et al., 2011; Lee et al., 1997; Hicks and Streeten, 1979). IM has declined dramatically in the developing world over the same period in which adoption of MVs increased globally: from 154 deaths per 1,000 live births in 1960 to 42 deaths in 2010. The diffusion of MVs could have contributed to the decrease in infant mortality if the subsequent yield increases led to improved maternal and infant nutrition, to increased incomes among farming families, or to decreases in the real price of food benefiting the entire population¹. An inspection of the relationship between MV diffusion and IM declines at the country-year level, however, does not yield a clear conclusion (Table 7). This is perhaps not surprising given the coarseness inherent in country level summaries of variables that display substantial sub-national heterogeneity, and the limited sample size. More fundamentally, correlations at the country level cannot be interpreted as a causal estimate, since a range of other variables could confound the impacts of MV diffusion. For example, a country experiencing rising incomes due to successful export manufacturing might enjoy rising incomes, raising the demand for food and profitability in the farming sector, incentivizing farmers to use more inputs (including MVs). Health might be improving as households can afford to spend more on health and the public health system improves with rising tax revenue. The association between

¹The vulnerability of rural households to food shortages is evident in the effect of large-scale feeding programs on anthropometric outcomes (Beaton et al., 1982), and in how rainfall shocks experienced by pregnant women in Indonesian farming communities affect their female children’s height, weight, and school completion as adults (Maccini and Yang, 2009). Agricultural technology improvements have been found to reduce the likelihood of households living below the poverty line in Mexico (Becerril and Abdulai, 2010), Ethiopia (Zeng et al., 2015), Rwanda and Uganda (Laroche et al., 2015)

increased MV use and declining infant mortality in this narrative does not represent the causal effect of MV diffusion.

Our statistical analysis compares trends in MV diffusion and IM declines across different locations in the same country in a sub-national difference-in-difference approach. We utilize sub-national variation in the rate of MV diffusion that arises from a combination of differences in the national rate of MV diffusion between crops, and geographical heterogeneity in cropping patterns. It then tests whether these temporal changes in MV diffusion are correlated with temporal changes in IM within countries, and pools results from all countries in the sample. By comparing rates of change in MV and IM, rather than their absolute levels (i.e. difference-in-differences estimation), while controlling for location specific fixed effects, we avoid basing our estimates on cross sectional comparisons across locations, which are highly susceptible to bias from confounding variables. And by only comparing trends in locations within the same countries (i.e by including country $\times$ year fixed effects), we implicitly control for all country-level, time changing variables that might have otherwise biased country-level analyses of the MV-IM relationship. This approach does not eliminate all possible causes of bias, but it dramatically reduces the scope for such bias when compared with a country-level analysis.

This paper is organized as follows. Section 2 describes data used. We provide details on the construction of local MV indicator in Section 3 and our empirical specification in Section 4. Results are reported in Section 5, and Section 6 concludes.

2 Data

2.1 Infant Mortality

Our main outcome variable, infant mortality, is measured through the Demographic and Health Surveys (DHS), which are the only high-quality, spatially-referenced, and internationally-comparable household surveys that provide detailed data on health of individuals. We compiled DHS data for developing countries in 5 regions: sub-Saharan Africa, Latin America, Middle East and North Africa, South East Asia and South Asia. Each mother is asked her fertility history, allowing for a record of 3 million children. We then restrict the data to rural areas and to mothers that have never migrated, since we are assigning the exposure of each child to MV diffusion according to their location. We focus on children born between 1961 and 2000, given the available data on MV diffusion data, described below. The resulting sample (once matched with the MV diffusion data) includes 18,142 villages in 438 administrative regions spread across 36 countries². The DHS are geo-referenced to roughly within 5 km, which can be spatially merged with crop distribution data allowing for an analysis at high spatial resolution. The DHS clusters in our study are mapped in Figure 1. Table 1 provides summary statistics for the data for children born around 1980 and around 2000. Infant mortality decreased in the data from 13% to 8% over these two decades, concurrently with increased diffusion in modern varieties across the developing world.

[Insert Figure 1: The locations of rural Demographic and Health Survey (DHS) clusters]

²The data are derived from 73 surveys and Table 8 shows the number of infants, country-wise, in our estimating sample.

[Insert Table 1: Summary statistics]

2.2 MV adoption

Historical data on MV diffusion are available by country from Evenson (2003a). The dataset (referred to as EGMV from here onwards) reports the fraction of area planted with modern varieties for each of 11 major crops (wheat, maize, rice, barley, pearl millet, sorghum, cassava, potato, groundnut, beans, and lentils) in 90 countries, at five-year intervals between 1960 and 2000 (Figure ?? and ?? illustrate the temporal and geographical coverage of MV diffusion data). Note that these are the important staple crops in terms of caloric intake, and cover 60% of cropland in our sample locations on average. We only use data for the 36 countries for which geo-referenced DHS data is available.

2.3 Crop area

We make use of spatially-explicit, global crop harvested area datasets to determine the relative crop mix in each location in each country. These data sets report the area cultivated with each crop in every location (pixel) of the world. We make use of this data to construct our proxy for localized MV diffusion rates (see below). Three dataset of this kind are available, as far as we are aware, and we conduct our analysis while using each of them, in turn, to assess the robustness of our results to the choice of the data. We note that the three data sets differ in terms of crops covered, data sources and methodology.

The first is the EarthStat (earthstat.org) dataset from Monfreda et al. (2008), which reports harvested area data circa 2000 (1997-2003) for 175 crops, 11 of which are of interest due to the availability of MV data. This dataset uses agricultural census and survey information to distribute crop harvested area across physical cropland areas, which are determined from remote sensing and agricultural census and survey information (Ramankutty et al. 2008). (Figure ?? provides a sample snapshot of data.)

The second dataset is the the Spatial Production Allocation Model (SPAM). Similar to the EARTH-STAT data, the SPAM maps are based on a collection of agricultural census and survey data, however the disaggregation to the grid cell is based on a modeling approach that includes information on cropland areas, biophysical crop suitability assessments, population density, and crop prices (You et al., 2014). SPAM2000 includes crop harvested area data for 10 crops with MV data. All three datasets are available at a five arc-minute resolution.

The third is the *historical* EarthStat crop harvested area dataset (Ray et al. 2012). This dataset is similar to the first one, except that it also reports yearly historical harvested area data from 1961-2008, but it only covers the three major cereal crops with MV data: maize, wheat, and rice (the dataset also includes soybean, but no MV data is available for this crop). The spatial and temporal frequency of the source data differs by country, and is not as complete as Monfreda et al. (2008). When historical subnational data was not collected for a specific country, the harvested area estimates are determined from the circa 2000 crop distribution data and historical national-level data. (Figure ?? provides a sample snapshot of data.)

3 Methodology

3.1 Construction of local MV Diffusion Indicators (MVDIs)

A central component of our analysis is the construction of a MV Diffusion Indicator (MVDI) at high spatial resolution. This indicator is constructed by combining the EGMV data with global high-resolution crop maps described above. Our approach is illustrated in Figure 2 in the case of Nigeria. The top rows map the spatial distribution of the six crops in the Monfreda data in 2000, showing the different distribution by crop (for example, maize is grown throughout, rice is more concentrated in the center of the country, and wheat is grown exclusively in the north). Below each map a graph shows the progression of MV diffusion at the national level by crop from the EGMV data. The bottom three maps show our composite MVDI for 1965, 1985 and 2000, constructed as explained below.

[Insert Figure 2: Crop distribution and modern variety data for Nigeria]

The MVDI is constructed in each grid cell and 5-year time step as the weighted average of crops' MV diffusion rate at that year (reported at the country level by Evenson and Gollin (2003b)), where the weights represent the relative share of cropped area in that grid cell devoted to that crop:

$$MVDI_{vct} = \frac{\sum_1^j (CropArea_{jvc} \times EGMV Area_{jct})}{\sum_1^j CropArea_{jvc}} \quad (1)$$

where v is a location (village) in country c and t is the period of observation. $EGMV Area_{jct}$ is the share of area cultivated with crop j that is planted with MVs in country c at time t , and $CropArea_{jvc}$ is the area cultivated with crop j in location v , as reported in the global crop maps (which are time invariant) mentioned above. The summation is conducted over all crops covered by the crop map in question. As explained above, we construct three variants of MVDI, using the three available global crop maps described above: the EARTHSTAT circa 2000 data from Monfreda et al. (2008), for which $j = 11$ (Barley, Beandry, Cassava, Groundnut, Lentil, Maize, Millet, Potato, Rice, Sorghum, Wheat); the SPAM dataset, for which $j = 10$ (Barley, Beandry, Cassava, Groundnut, Maize, Millet, Potato, Rice, Sorghum, Wheat); and the historical EARTHSTAT data from Ray et al. (2012), for which $j = 3$ (Maize, Rice, Wheat)³. (Figure ?? and ?? illustrate the variation in the constructed MVDI variables.)

These MVDI variables will be used as proxies for the actual, but unobserved, local rate of MV diffusion in our empirical analysis. For the analysis to be interpreted correctly, these constructed diffusion rates should be highly correlated with actual diffusion rates. It is of course impossible to test this directly because local MV diffusion rates are not observed globally. However, we can perform two partial tests.

First, it is evident from the construction of the variables that two sufficient conditions for this to hold are (a) fraction of areas devoted to various crops should remain well correlated over time, and (b) the share of the area cropped with a MV, for each crop and location, should not be substantially higher in areas that were not cropped with the crop in question in 1965 than in those that were (in other

³Figure 8 and Figure 7 illustrate the crop area and MVDI maps based on EARTHSTAT 1961-65 and SPAM 2000 respectively.

words, initial cropping patterns matter for subsequent MV adoption). Condition (a) can be verified by checking the correlation of grid cell crop areas between 1965 and in 2000 for countries in our sample with historical sub-national census records as reported by Ray et al (2012). The correlation is 0.92 in the case of maize, 0.57 in the case of wheat, and 0.95 in the case of rice, suggesting little variation in the spatial crop mix of main staple crops over time.

Second, we can test the validity of the proxy in locations in which local MV diffusion rates were measured over time. Even though India is not included in our sample of analysis (since geo-referenced DHS data is not available there in the time period of the analysis), data on MV use is available at the district/admin 2 level from 1960-2000 (ICRISAT 2013). Comparing this data to our constructed proxy reveals a high degree of correlation between actual MV diffusion rates and both variants of our MV indicator (Figure 9).

4 Empirical specification

We estimate the following regression model:

$$y_{ivct} = \gamma MDVI_{vct} + u_v + Z_{ct} + X_{ivct} + e_{ivct} \quad (2)$$

where, y is a binary indicator of infant mortality observed for child i , in village (sample cluster) v , in country c and in year t . $MDVI_{vct}$ is the constructed indicator of MV diffusion in the grid cell to which village v belongs, country c and year t . X is a vector of child level controls that includes the child's sex and a quadratic function of the mother's age. The regression controls for village fixed effects u_v and country $\times$ year fixed effects, Z_{ct} (one fixed effect for each combination of country and year).

Our model tests whether a child born when MV diffusion was higher has a different mortality risk than a statistically identical child born in the same village in a different year when MV diffusion was lower. This is accomplished by including an extensive set of 'fixed effects', i.e. collection of binary variables that flexibly control for categories of potentially unobservable confounders. We include a range of binary indicators u_v for each village (DHS sampling cluster) that absorb all time-invariant village characteristics that could confound inference, such as climate or soils or distance to the capital city. Including these fixed effects in the regression ensures our estimates are based on variation in MV diffusion within villages, over time, rather than across villages. We also include flexible time trends at the country level, represented by binary indicators Z_{ct} for each combination of country and year. These absorb any time-varying confounders that are defined at the country level, including national policy changes. Including these 'fixed effects' in the regression ensures our estimates are based on comparisons of changes in MV between villages located in the same country.

The term e_{ivct} represent idiosyncratic errors. Our estimates cluster standard errors at the admin-1 level (there are 434 state-level administrative zones in the 37 countries in our data). This procedure accounts for possible correlation in these error terms across any two observations that are located in the same administrative region of a given country, correcting biases in standard errors that arise from spatial correlation in the treatment variable as well as temporal autocorrelation in the outcome

variable Bertrand et al. (2004).

The coefficient of interest is γ which we hypothesize to be negative if increases in MV diffusion lead to reductions in IM. It is important to note that the diffusion of MVs was accompanied by increases in crop inputs (Tilman et al. 2002, Pingali 2012). Our estimate of MV diffusion implicitly includes the yield-enhancing effects of input intensification that accompany the use of MVs. Therefore, effects on health should not only be considered a response to the MVs themselves, but to the wholesale adoption of more intensive and productive cropping practices stimulated by the use of MVs. A second point is that our indicator tracks replacement of traditional crop varieties with modern varieties. Additional crop yield and human welfare benefits would be expected as more advanced modern varieties replace earlier varieties, but our approach only measures the average health impact across all types of modern varieties that were adopted.

Our empirical strategy estimates a ‘reduced-form’ relationship, meaning it does not allow us to directly identify the mechanism driving the relationship. The two primary candidate mechanisms include a direct effect on the income of farmers resulting from increased yields, or through improved food intake of both mothers and infants due to increased food availability. Since our estimates reflect differences in the rates of IM declines across villages in the same country, they can only capture those impacts of MV diffusion that are localized in nature. In particular, increases in yields that result in uniform declines in food prices across an entire country would be ‘missed’. Only localized relative changes in income and food prices would be captured by our estimates, which are therefore a lower bound. We note, however, that imperfect market linkages in developing countries make the possibility of localized price changes quite likely (Ravallion, 1986).

We estimate the above regression model independently using each of the two variants of the MV indicators described above. The variant using 1965 cropped areas generates a more exogenous sub-national proxy for MV diffusion, since subsequent crop distributions might shift as a response to MV availability. On the other hand, using the 2000 cropped areas allow us to include more crops in the analysis, and sidesteps data quality issues in the construction of 1965 cropland area maps in countries lacking agricultural census data in that time period.

In addition to estimating effects on total IM, we also report gender separated impacts for two reasons. First, male infants consistently exhibit higher mortality rates than females, especially in response to in-utero stress (Almond and Currie, 2011) (Almond and Mezmurder, 2011; Almond and Currie, 2011). Many scholars attribute the difference to males being biologically weaker (Naeye et al. 1971) and more susceptible to disease than female infants due to a more vigorous immune response among females (Bouman et al 2005, Read et al 1997, Waldron 1983), though the size of the biological effect is contested (Pongou, 2012). Second, differences in the impacts of household income fluctuations on boys and girls are routinely observed in developing countries, and typically thought by development scholars to arise from prevalent gender biases in intra-household resource allocation. Evidence from several studies indicates that households often prioritize boys over girls in difficult times (Dreze and Sen, 1989) (Dreze and Sen, 1989; Jayachandran, 2005; Maccini and Yang, 2008; Baird, Friedman and Schady, 2011), including in terms of nutrient allocation (Behrman, 1988; Behrman and Deolalikar, 1990).

5 Results

Table 2 reports estimates of the effect of MV diffusion on IM derived from regression (2). Columns 1-3 reports estimates derived by using the three variants of MDVI that are constructed from the three global crop maps described above.

Column (1) reports estimates derived by using the EARTHSTAT global crop map (2000 crop mix for 11 crops). The results indicate that across both sexes (panel A) children were less likely to die in infancy when born in places with higher MV use. The magnitude of the estimate suggests that an increase of MV diffusion rates from 0% (no MV) to 100% (full MV coverage) is associated with a 6% decline in infant mortality (down from a sample mean of 10%). A one standard deviation increase (14%) in the rate of MV diffusion is associated with a 0.9% decline in infant mortality.

Columns (2) and (3) report parallel estimates derived by using the SPAM and historical EARTHSTAT global crop maps, respectively. The results remain qualitatively similar. Column (3) constitutes our preferred specification, since crop areas are observed in 1965, reducing concerns about endogenous changes in crop mix resulting from MV diffusion.

Panel B limits the sample to female infants. The three regressions suggest that the effect of MV diffusion on the mortality of infant girls is negative, but lower than the overall effect and statistically imprecise. Panel C reports results for males and finds impacts that are large and precise. The coefficients across the three models range from 0.094 – 0.080, suggesting that males born when MV diffusion is 1 standard deviation higher benefit from a 1.1 – 1.3 percentage point reduction in mortality risk (compared to a mean value of 11% mortality rate in the male sample). These results suggest that the benefit of MV diffusion, whether through improved nutrition or higher incomes, improves the health of male infants more than that of female infants. We test whether the salubrious effect occurs in the womb by comparing the male-to-female infant sex ratio in years before and after MV diffusion, and find only weak evidence that MV diffusion led to an increase in the sex ratio (Table S1). This suggests that the health effects on infant mortality, in particular those detected among males, occur not by changing the rate of miscarriage of male fetuses compared to female fetuses but by improving the health of fetuses and infants that were already going to result in a live birth in the absence of MVs.

[Insert Table 2: The impact of modern variety (MV) diffusion on the mortality of all infants]

Table 3 compares results across regions, using the 1965 crop mix specification reported in column (3) of Table 2. The results indicate that the infant mortality decline triggered by modern variety diffusion is mainly driven by Latin America, the Middle East & North Africa (MENA), and Sub-Saharan Africa. The magnitude of the effect is substantially larger in Latin America (~5x) and MENA (~8x) than in Sub-Saharan Africa. In all three regions, the beneficial effect of MV diffusion on infant health is mostly only evident in the case of male infants (the effect on females is only statistically significant in MENA).

We do not find indication that MV diffusion in South and Southeast Asia (SSEA) lead to reductions in infant mortality. While this may seem puzzling (given that the Green Revolution success stories

are often from Asian countries), there are several reasons why our ability to detect a relationship is compromised in SSEA. First, we note that our sample size of countries SSEA is limited, since only Bangladesh, Nepal, and the Philippines provide geo-referenced DHS data. Second, these countries are dominated by rice cropping; since variation in our constructed MV indicator relies upon geographical heterogeneity in the crop mix, the dominance of rice may limit the variation of our explanatory variable and thus lead to imprecise estimates. For the three major cereals represented in the Ray et al. (2012) dataset, 69% of harvested area was devoted to rice in 1997-2003 (FAOSTAT), and in Bangladesh it was as high as 93%. Among all 11 crops with MV data, 63% of harvested area was devoted to rice (FAOSTAT). Since variation in the constructed MVDI indicator relies upon geographical heterogeneity in the crop mix, the dominance of rice may limit the variation of the explanatory variable and thus result in less precise estimates. The root mean square error in the MVDI (after removing village fixed effects and time trends as in our main specifications) reveals that the observations in SSEA exhibit less than half as much variation in the MVDI compared to other regions. Third, we note that the children in the sample were mostly born after the diffusion of MV technologies in Asia (the median baby in the sample was born in 1991, and 90% of babies were born after 1980). By 1990, Bangladesh already had 60% of wheat and 40% of rice planted to MVs, Nepal had 80% of wheat and 30% of rice planted to MVs, and the Philippines had 90% of rice planted to MVs. The large infant health gains due to MV diffusion may therefore have already happened by the time our data begin.

[Insert Table 3: The impact of modern varieties on infant mortality by region]

5.1 Robustness Tests

Our empirical strategy provides a substantial improvement over inference based on country level variation. Using sub-national data on MV diffusion and IM allows us to flexibly control for all unobservables occurring at the country level (through the inclusion of interacted country $\times$ year fixed effects). Still, variation in MV diffusion is clearly not purely exogenous, making it impossible for us to eliminate all possible sources of bias.

One threat to identification is that individual level characteristics could be confounding the effects of MVDI and those are really the characteristics driving the decline in infant mortality. Our results are robust to inclusion of birth order fixed effects and mother fixed effects. To be clear, the inclusion of the latter allow us to compare children born to the same mother with different exposure to MVDI. Table 5 show that the qualitative story of the paper's main finding still holds.

[Insert Table 4 and 5: Robustness of the impact of modern varieties on infant mortality to birth order and mother fixed effects]

Another principal potential threat to causal inference lies with the possibility that localized (sub-national) improvements in both MV diffusion and IM are in fact driven by localized variation in economic growth rates. If incomes increase at higher rates in certain sub-national regions, one may be concerned that they lead to both declines in IM as well as higher ability to invest in improved seeds and associated inputs, leading us to wrongly infer a causal connection between the two variables. While we do not observe local incomes at the required spatial and temporal resolution, and therefore are unable to fully account for this possibility, we subject our model to few robustness tests in which

we flexibly control for interaction between regional flexible time trends and geographical attributes of each location that are often predictive of economic growth: distance to the coast and distance to cities. In other words, we estimate

$$y_{ivct} = \gamma MVDI_{vct} + u_v + Z_{ct} + X_{ivct} + W_{R,t}^{(1)} \times D_{vc}^{Coast} + W_{R,t}^{(2)} \times D_{vc}^{City} + e_{ivct} \quad (3)$$

where all terms are as above, and we add interactions between region $\times$ year fixed effects $W_{R,t}^{(i)}$ and the distance of each village from both the coast and the nearest major city (D_{vc}^{Coast} and D_{vc}^{City}). This model isolates the effect of MV diffusion from any region specific flexible time trends that differentiate locations on the basis of their distance to coast or urban centers, and should therefore be able to capture flexibly much of the local patterns of economic growth within countries. Results are reported in column (4) of Table 2 and show that these controls have little effect on our estimates.

A third type of potential concern has to do with the possibility that the local crop mix itself has an impact on declines in IM that is not driven by the diffusion of MVs, but by some other attribute of the crop mix, or its correlate. For example, one might imagine that differing trends in the prices of specific crops are creating different trends in incomes for some locations. If these price trends are correlated with MV diffusion rates across crops, the effect on IM might be driven by price changes rather than by MV diffusion. To address this possibility, we test the robustness of our estimates to the inclusion of interactions between flexible region specific time trends of each crop and the local crop mix (observed in 1965). In other words, we estimate:

$$y_{ivct} = \gamma MVDI_{vct} + u_v + Z_{ct} + X_{ivct} + \sum_j \alpha_j W_{R,t}^{(j)} \times CropArea_{jvc} + e_{ivct} \quad (4)$$

where all terms are as above, and we add interactions between crop specific region year fixed effects $W_{R,t}^{(j)}$ and the cropped area of each crop j in the location in question, for all crops in the data. Results are reported in column (5) of Table 2 and show that these controls have little effect on our estimates.

Finally, critics may argue that it's possible that there are some other factors other than MV diffusion such as the global spread of Maternal, Neonatal and Child Health (MNCH) Interventions that are responsible for our findings. While data constraints do not explicitly allow us to control for these variables (because such questions were not asked for children with respect to their birth year), we are able to construct averages of proxies of health interventions at the village level for survey year and test for correlation between our MVDI variable and these interventions. We find weak correlation between MVDI and health interventions and no evidence for any correlation with vaccination or breastfeeding (see Table 10 and Table 11).

6 Discussion

In the year 2000, around 114 million baby boys were born in the developing world (UN Population Division World Population Prospects 2015). The population-weighted average of crops planted to modern varieties by country was 63%. Our estimates suggest that this level of MV diffusion reduced the mortality rate of male infants by 5-6 percentage points, which translates into 15-18 million infant

deaths averted per year by the year 2000. The region-specific results suggest that of Latin America's 29 million male infants in 2000, the 61% coverage of MVs for major crops averts 3.8 million infant deaths; in the Middle East & North Africa, the MV diffusion of 40% reduces infant risk by 12 percentage points, averting 2.9 million male infant deaths. The estimate for sub-Saharan Africa suggests that the MV diffusion in 2000 of 32% reduced infant mortality risk by 2 percentage points, averting 1.4 million male infant deaths.

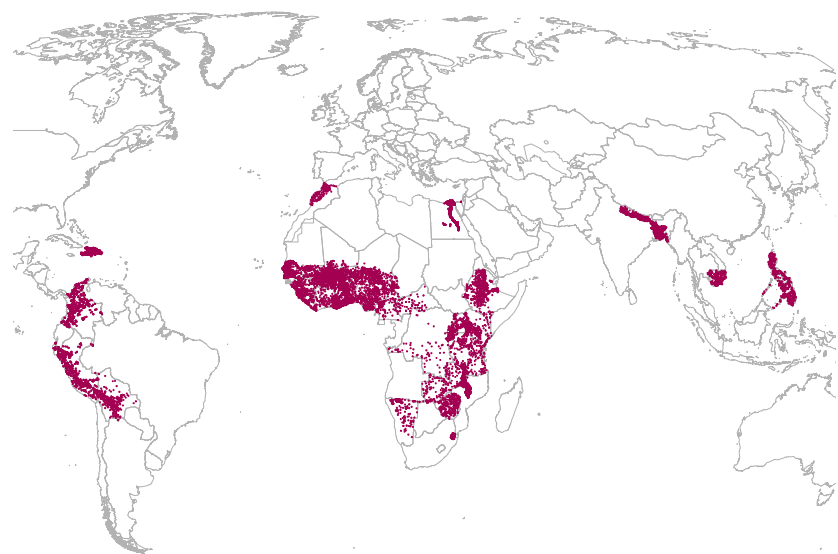
Our results suggest that the diffusion of MVs contributed to improvements in infant health, particularly in poorer households/regions (see Figure 3-Figure 6). Although recent discussions on malnutrition rightly put great emphasis on micro-nutrient supplementation and production (DeFries et al., 2015), our results suggest that the health benefits from broad-based increases in agricultural yields should not be forgotten. Our results indicate that the health effects of MV diffusion differed based on the sex of the infant. The greater reduction in infant mortality seen for infant boys than infant girls may result from discrimination among parents in allocating scarce resources to children. Alternatively, infant boys may benefit more than girls from improved maternal and infant nutrition due to biological characteristics that contribute to underlying differences in IM rates between the sexes. Identifying which of these mechanisms is at work remains an avenue of future research to inform policy decisions and public investments in agricultural regions of the developing world.

The aggressive non-parametric controls in our estimation significantly reduce the assumptions required to interpret results as the causal effect of MV diffusion on infant mortality. Potentially confounding factors would have to be correlated with crop distribution patterns as well as changes in mortality, and vary in time at the village level in ways that are distinct from changes in national averages over time. For instance, improvements in road access may correlate both with MV adoption (say, through the availability of seeds and other inputs and information) and with infant mortality (for instance, through greater income opportunities to generate income through trade, or better access to vaccines). However, since we use crop distribution to proxy for MV adoption at the village level, in order to confound our estimate the increased access to roads would have to coincide with a national-level increase in modern variety use for a particular crop, be connecting villages growing that particular crop back in 1965, and coincide with a reduction in those villages' infant mortality rate. While these assumptions are not benign, they are significantly weaker than study designs which look simply at the association over time of MV diffusion and other outcomes.

Our results provide striking evidence for the human welfare benefits of agricultural productivity growth via the mechanism of reducing infant mortality. Continued investments in agricultural research and development could therefore lead to substantial human welfare benefits in areas where rates of MV diffusion (Evenson and Gollin, 2003a; Walker and Alwang, 2015) (Evenson 2003, Walker et al. - DIIVA book chapter 19), input intensity (Mueller et al., 2012; Lassaletta et al., 2014), and crop productivity Mueller et al. (2012); van Ittersum et al. (2013); Mueller and Binder (2015) (Mueller et al. 2012, van Ittersum et al. 2012, Mueller et al. 2015) remain low. These health gains, coupled with evidence of the effect of agricultural intensification on reducing cropland expansion and greenhouse gas emissions (Burney et al., 2010; Lobell et al., 2013; Hertel et al., 2014), furthers the case for continued investment in development and diffusion of technologies to raise agricultural productivity.

A Figures

Figure 1: The locations of rural Demographic and Health Survey (DHS) clusters



Note: The sample covers 18,382 total villages

Figure 2: Construction of MVDI (EarthStat 2000): A Country Example

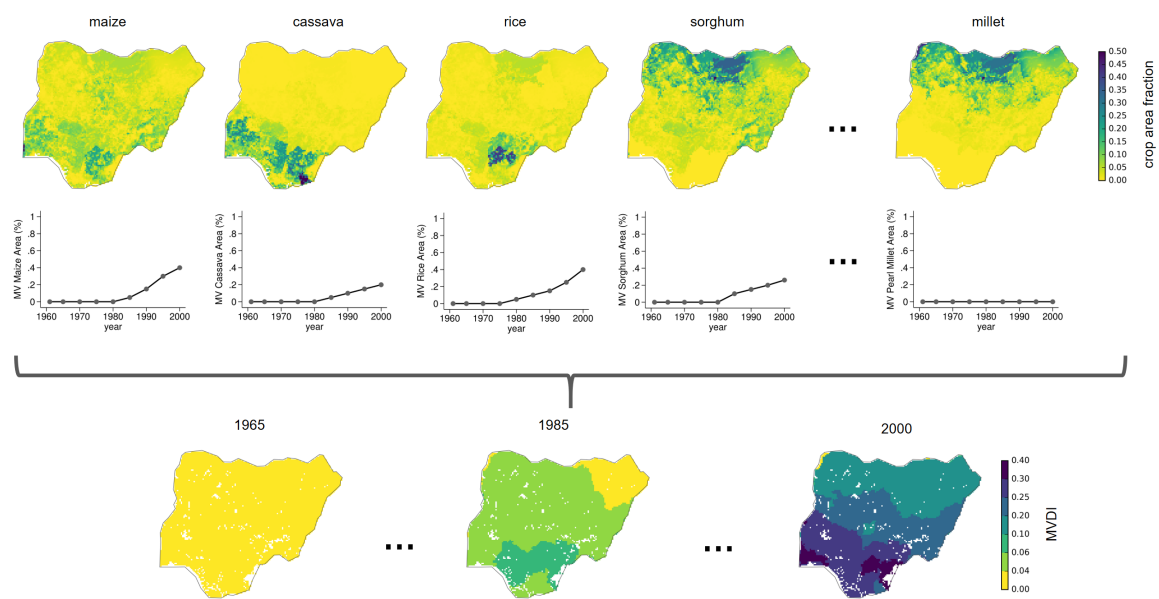


Figure 3: Heterogeneous impacts of MVs on IM, by irrigation

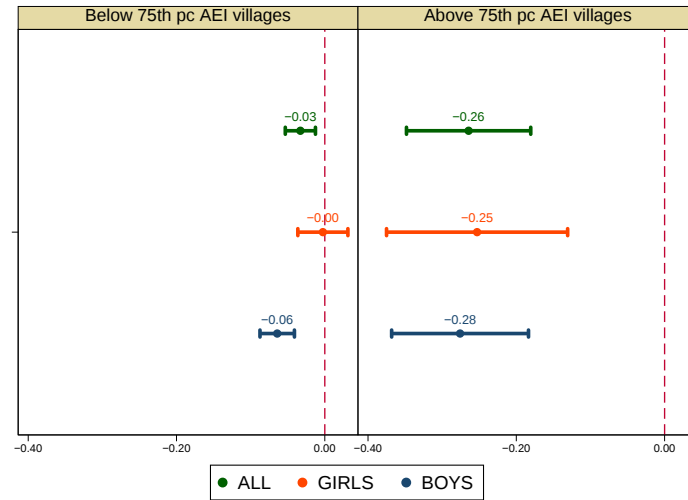


Figure 4: Differential impacts of MVs on IM, by market access

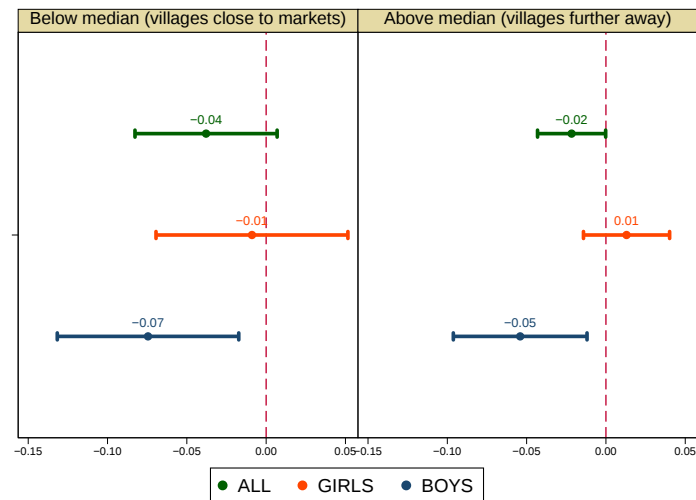


Figure 5: Differential impacts of MVs on IM, by mother's education

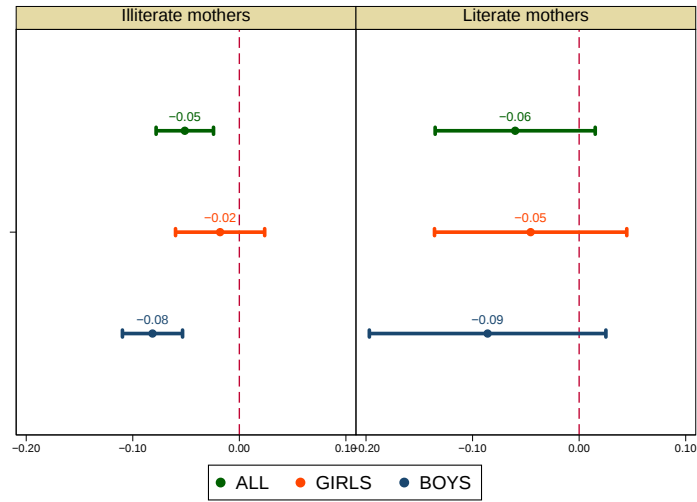
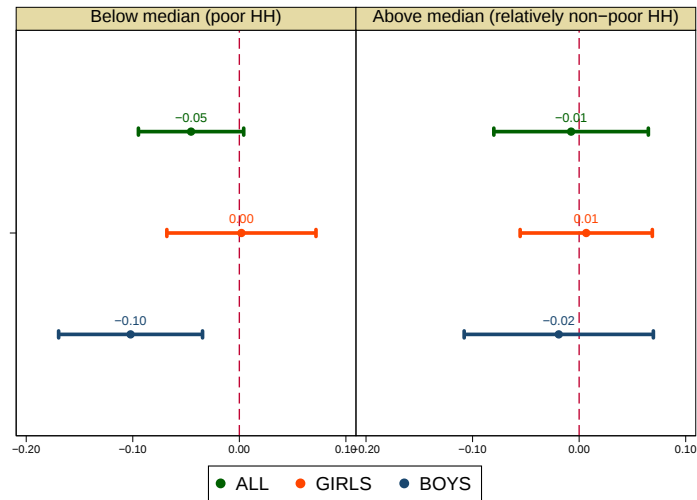


Figure 6: Differential impacts of MVs on IM, by DHS asset index



B Tables

Table 1: Summary statistics

	<i>Around 1980s</i>			<i>Around 2000s</i>		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
<i>Outcome</i>						
Infant Mortality: All	0.13	0.33	73.659	0.08	0.27	73.925
Infant Mortality: Girls	0.12	0.32	35.652	0.08	0.26	36.315
Infant Mortality: Boys	0.13	0.34	38.007	0.09	0.28	37.610
<i>Treatment (MVDI)</i>						
Earthstat (circa 2000)	0.07	0.09	71.939	0.21	0.17	71.357
SPAM (circa 2000)	0.06	0.09	69.635	0.20	0.19	69.391
Earthstat (1961-65)	0.09	0.14	70.131	0.28	0.24	70.353
<i>Controls</i>						
Sex ratio	0.52	0.50	73.659	0.51	0.50	73.925
Mother's age at birth	22.40	5.02	73.659	26.26	6.91	73.925

Note: Around 1980s refers to 1978-82 and around 2000s refers to 1998-2000

Table 2: Impact on infant mortality

	(1)	(2)	(3)	(4)	(5)
Panel A: All					
MV $\times$ 2000 area	-0.0633 (0.0266)**	-0.0467 (0.0174)***			
MV $\times$ 1961-65 area			-0.0542 (0.0165)***	-0.0553 (0.0172)***	-0.0413 (0.0155)***
N	580,805	562,003	567,941	518,179	384,786
Mean	.1	.1	.1	.11	.1
Panel B: Girls					
MV $\times$ 2000 area	-0.0212 (0.0365)	-0.0298 (0.0237)			
MV $\times$ 1961-65 area			-0.0238 (0.0228)	-0.0291 (0.0248)	-0.0122 (0.0253)
N	282,395	273,335	276,160	251,790	187,111
Mean	.098	.097	.098	.1	.098
Panel C: Boys					
MV $\times$ 2000 area	-0.0939 (0.0309)***	-0.0556 (0.0247)**			
MV $\times$ 1961-65 area			-0.0859 (0.0185)***	-0.0797 (0.0175)***	-0.0658 (0.0176)***
N	297,083	287,411	290,475	265,271	196,906
Mean	.11	.11	.11	.11	.11
Geog controls	No	No	No	Yes	No
Area controls	No	No	No	No	Yes

Note: Each estimate in Table 2 represents γ from the following estimating equation: $y_{ivct} = \gamma MDVI_{vct} + u_v + Z_{ct} + X_{ivct} + e_{ivct}$ where, y_{ivct} is a binary indicator of infant mortality (death in the first year of life) i.e. whether child i in village v in country c died in its birth year t ; u_v are village fixed effects and Z_{ct} are country $\times$ year FE; X_{ivct} includes quadratic in mother's age (at birth of child) and sex of child; and e_{ivct} clustered at subnational (admin) level. The sample is restricted to rural villages and mothers who report to have never migrated. Geographic controls include distance to coast $\times$ region $\times$ year FE and distance to cities $\times$ region $\times$ year FE as noted in Equation 3. Area controls include cropped area $\times$ region $\times$ year FE as described in Equation 4.

Table 3: Impact of MV (Crop area in 1961-65 x MV) on infant mortality, by region

	(1) LAC	(2) MENA	(3) SSA	(4) SSEA
All	-0.1493 (0.0643)**	-0.2367 (0.0663)***	-0.0280 (0.0125)**	0.1360 (0.1173)
N	76,224	119,047	316,728	55,942
Mean	.075	.095	.12	.097
Girls	-0.1074 (0.0764)	-0.1953 (0.0891)**	0.0023 (0.0209)	-0.0386 (0.1618)
N	37,044	57,469	154,458	27,189
Mean	.069	.094	.11	.09
Boys	-0.2156 (0.0884)**	-0.2873 (0.0621)***	-0.0571 (0.0141)***	0.2084 (0.1757)
N	38,770	61,520	161,675	28,510
Mean	.081	.097	.12	.11

Note: Table 3 presents estimates of γ when the following estimating equation is run for each region k separately: $y_{ivct}^k = \gamma(MVDI(1961 - 65, Area))_{vct}^k + u_v + Z_{ct} + X_{ivct} + e_{ivct}$ where, y_{ivct} is a binary indicator of infant mortality (death in the first year of life) i.e. whether child i in village v in country c died in its birth year t ; u_v are village fixed effects and Z_{ct} are country $\times$ year FE; X_{ivct} includes quadratic in mother's age (at birth of child) and sex of child; and e_{ivct} clustered at subnational (admin) level. The sample is restricted to rural villages and mothers who report to have never migrated. LAC includes 5 countries (Bolivia, Columbia, Dominican Republic, Haiti and Peru), North Africa 2 countries (Egypt and Morocco), SSA 25 countries (Benin, BurkinaFaso, CAR, Cameroon, CongoDRC, Cote-d'Ivoire, Ethiopia, Ghana, Guinea, Kenya, Liberia, Malawi, Mali, Namibia, Niger, Nigeria, Rwanda, Senegal, SierraLeone, Swaziland, Tanzania, Togo, Uganda, Zambia and Zimbabwe) and SSEA 4 countries (Bangladesh, Cambodia, Nepal and Philippines).

Table 4: Robustness: Birth order FE

	(1) EARTHSTAT (circa 2000)	(2) SPAM (circa 2000)	(3) EARTHSTAT (1961-1965)
<i>Panel A: All</i>			
MVDI	-0.0628 (0.0265)**	-0.0488 (0.0176)***	-0.0550 (0.0161)***
N	580,805	562,003	567,941
Mean	.1	.1	.1
<i>Panel B: Girls</i>			
MVDI	-0.0200 (0.0359)	-0.0331 (0.0239)	-0.0245 (0.0220)
N	282,395	273,335	276,160
Mean	.098	.097	.098
<i>Panel C: Boys</i>			
MVDI	-0.0944 (0.0313)***	-0.0574 (0.0248)**	-0.0870 (0.0186)***
N	297,083	287,411	290,475
Mean	.11	.11	.11

Note: Each estimate in Table 4 represents γ from the following estimating equation: $y_{ivct} = \gamma MDVI_{vct} + u_v + Z_{ct} + X_{ivct} + e_{ivct}$ where, y_{ivct} is a binary indicator of infant mortality (death in the first year of life) i.e. whether child i in village v in country c died in its birth year t ; u_v are village fixed effects and Z_{ct} are country $\times$ year FE; X_{ivct} includes quadratic in mother's age (at birth of child), sex of child and birth order fixed effects; and e_{ivct} clustered at subnational (admin) level. The sample is restricted to rural villages and mothers who report to have never migrated.

Table 5: Robustness: Mother FE

	(1) EARTHSTAT (circa 2000)	(2) SPAM (circa 2000)	(3) EARTHSTAT (1961-1965)
<i>Panel A: All</i>			
MVDI	-0.0768 (0.0262) ^{***}	-0.0429 (0.0231) [*]	-0.0478 (0.0184) ^{***}
N	557,561	539,508	545,210
Mean	.11	.1	.11
<i>Panel B: Girls</i>			
MVDI	-0.0313 (0.0380)	-0.0340 (0.0332)	-0.0070 (0.0309)
N	242,963	235,130	237,550
Mean	.1	.1	.1
<i>Panel C: Boys</i>			
MVDI	-0.1253 (0.0318) ^{***}	-0.0515 (0.0302) [*]	-0.0753 (0.0206) ^{***}
N	258,741	250,279	252,932
Mean	.11	.11	.11

Note: Each estimate in Table 5 represents γ from the following estimating equation: $y_{ivct} = \gamma MDVI_{vct} + u_v + Z_{ct} + X_{ivct} + e_{ivct}$ where, y_{ivct} is a binary indicator of infant mortality (death in the first year of life) i.e. whether child i in village v in country c died in its birth year t ; u_v are village fixed effects and Z_{ct} are country $\times$ year FE; X_{ivct} includes quadratic in mother's age (at birth of child), sex of child and mother fixed effects; and e_{ivct} clustered at subnational (admin) level. The sample is restricted to rural villages and mothers who report to have never migrated.

C Supplementary tables and figures

Figure 7: Construction of MVDI (SPAM 2000) for Nigeria

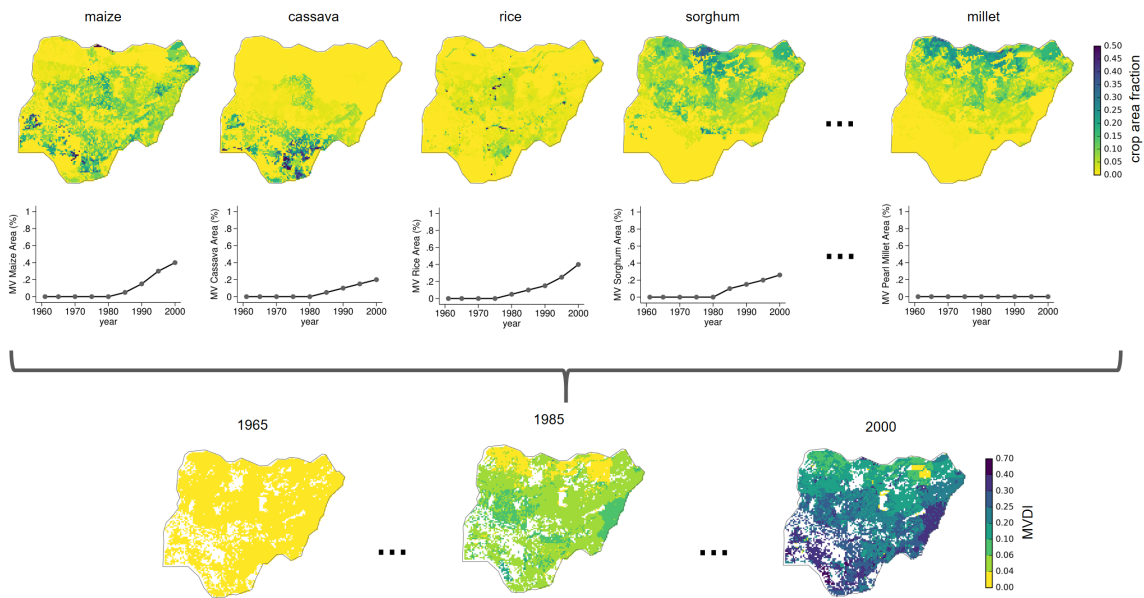


Figure 8: Construction of MVDI (EarthStat 1961-65) for Nigeria

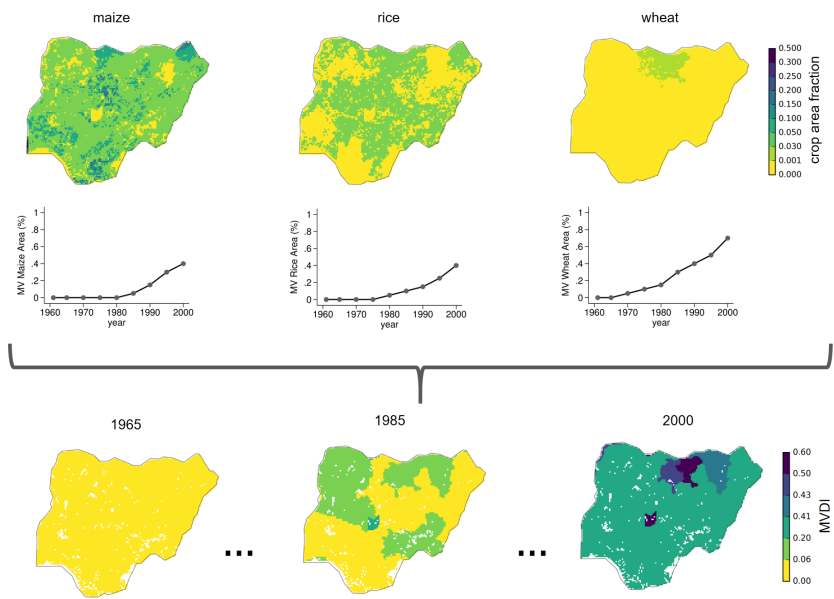
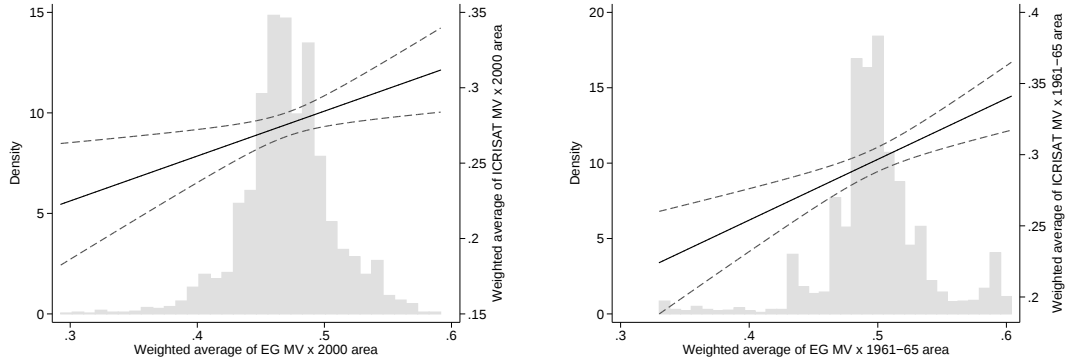


Figure 9: Validation of MV Diffusion Variable using Subnational Data from India



Note: Figure 9 illustrates the correlation between the MVDI indicator calculated using alternative cropped area datasets.

Table 6: Validation of MV Diffusion Variable using Subnational Data from India

	(1)	(2)
MVDI (2000 area)	0.2978 (0.0953) ^{***}	
MVDI (1961-65 area)		0.4272 (0.1130) ^{***}
N	2,408	2,408

Note: Table 6 presents results for: $y_{dt}^j = \beta MVDI_{dt}^j + u_d + v_t + e_{dt}$ where, y_{dt} is the MVDI in district d at time t (constructed using actual district-level data from ICRISAT, 2013); $(MVDI^j)_{dt}$ is the constructed MVDI variable using Equation 1 in district d at time t [$j = 3$ (Rice, Wheat, Maize) or $j = 5$ (Rice, Wheat, Maize, Sorghum, Millet)]; u_d are district fixed effects and v_t are year FE; and e_{dt} is the idiosyncratic error term that is clustered at district level.

Table 7: Country-Level Association of MV Diffusion and Infant Mortality

	(1)	(2)	(3)	(4)
MV (11 crops)	52.99 (18.36) ^{***}		10.80 (40.04)	
MV (cereals)		29.06 (13.78) ^{**}		−31.20 (34.71)
N	700	700	700	700
Countries	86	86	86	86
Region × year FE	Yes	Yes	No	No
Country specific trends	No	No	Yes	Yes

Note: Table 7 presents results for the following estimating equation: $y_{ct} = \gamma(WeightedMV)_{ct} + u_c + f(t) + e_{ct}$ where, y_{ct} is the infant mortality in country c at time t (number of infants dying per 1,000 births); $(WeightedMV)_{ct} \in \{11crops, cereals\}$ is the crop area weighted MV adoption in country c at time t for 11 crops (Barley, Cassava, Groundnut, Lentil, Maize, Bean, Millet, Rice, Sorghum, Wheat and Potato) or 5 cereals (Maize, Millet, Rice, Sorghum and Wheat); u_c are country fixed effects and $f(t)$ are region-year FE or country specific linear time trends; and e_{ct} is the idiosyncratic error term that is clustered at country level. The data is sourced from Evenson and Gollin (2003b).

Table 8: Summary of number of surveys and infants in estimating sample, by country

Country	Nsurveys	Girls	Boys	Total
LAC-BOL	1	2,699	2,742	5,441
LAC-COL	1	3,623	3,757	7,380
LAC-DOM	1	6,418	6,848	13,266
LAC-HTI	2	8,670	9,000	17,670
LAC-PER	2	16,158	16,949	33,107
MENA-EGY	6	54,729	58,534	113,263
MENA-MAR	1	2,814	3,030	5,844
SSA-BEN	2	5,484	5,835	11,319
SSA-BFA	3	11,252	11,910	23,162
SSA-CAF	1	2,359	2,439	4,798
SSA-CIV	1	2,199	2,181	4,380
SSA-CMR	2	2,729	2,806	5,535
SSA-COD	1	1,546	1,718	3,264
SSA-ETH	2	18,735	20,233	38,968
SSA-GHA	4	4,872	5,185	10,057
SSA-GIN	1	4,962	5,367	10,329
SSA-KEN	2	2,440	2,717	5,157
SSA-LBR	2	1,969	2,184	4,153
SSA-MLI	3	20,828	21,862	42,690
SSA-MWI	3	20,781	21,177	41,958
SSA-NAM	2	2,724	2,663	5,387
SSA-NER	2	8,495	8,850	17,345
SSA-NGA	3	17,714	18,711	36,425
SSA-RWA	1	1,884	1,899	3,783
SSA-SEN	4	13,571	14,174	27,745
SSA-SLE	1	1,469	1,609	3,078
SSA-SWZ	1	538	506	1,044
SSA-TGO	2	3,318	3,419	6,737
SSA-TZA	2	2,672	2,625	5,297
SSA-UGA	2	3,050	3,086	6,136
SSA-ZMB	1	1,404	1,350	2,754
SSA-ZWE	2	3,379	3,434	6,813
SSEA-BGD	3	4,657	4,826	9,483
SSEA-KHM	2	16,584	17,277	33,861
SSEA-NPL	2	2,633	2,731	5,364
SSEA-PHL	2	3,726	4,086	7,812
Total	73	283,085	297,720	580,805

Note: Table 8 shows the number of surveys and infants (boys and girls) in the estimating sample.

Table 9: Impact of MV on sex ratio

	(1)	(2)	(3)
MV $\times$ 2000 area	0.0640 (0.0351)*		
MV $\times$ 1961-65 area		-0.0079 (0.0192)	0.0016 (0.0202)
N	580,805	567,941	518,179
Mean	.51	.51	.51
Geog controls	No	No	Yes

Note: Table 9 presents results for the following estimating equation: $y_{ivct} = \gamma MDVI_{vct} + u_v + Z_{ct} + X_{ivct} + e_{ivct}$ where, y_{ivct} is a binary indicator that measures sex ratio (boys to girls) i.e. whether child i in village v in country c at birth year t is a boy or not; u_v are village fixed effects and Z_{ct} are country $\times$ year FE; X_{ivct} includes quadratic in mother's age (at birth of child); and e_{ivct} clustered at subnational (admin) level. The sample is restricted to rural villages and mothers who report to have never migrated. Geographic controls include distance to coast $\times$ region $\times$ year FE and distance to cities $\times$ region $\times$ year FE.

Table 10: Association between MVDI and Maternal, Neonatal and Child Health Interventions at the village level

	(1) EARTHSTAT (circa 2000)	(2) SPAM (circa 2000)	(3) EARTHSTAT (1961-1965)
Panel A: Access to health care			
MVDI	0.0117 (0.1392)	0.0781 (0.0753)	0.2520 (0.1474)*
N	1,738	1,718	1,724
Mean	.43	.42	.43
Panel B: ANC visits			
MVDI	0.9870 (0.5357)*	0.5897 (0.3510)*	0.1792 (0.3750)
N	5,391	5,272	5,255
Mean	2.2	2.2	2.2
Panel C: Institutional delivery			
MVDI	-0.0142 (0.1044)	-0.0125 (0.0633)	-0.1603 (0.0783)**
N	5,426	5,303	5,290
Mean	.26	.26	.26
Panel D: Breastfeeding			
MVDI	-0.0098 (0.0544)	-0.0175 (0.0303)	0.0587 (0.0374)
N	5,654	5,521	5,511
Mean	.3	.3	.3
Panel E: Vaccination			
MVDI	-0.0240 (0.0622)	0.0219 (0.0254)	-0.0442 (0.0570)
N	5,209	5,093	5,114
Mean	.8	.81	.8

Note: Table 10 presents results for the following estimating equation: $y_{vct} = \gamma MVDI_{vct} + u_a + Z_{ct} + e_{vct}$ where, y_{vct} is a measure of Maternal, Neonatal and Child Interventions (MNCH) in village v in country c in survey year t ; u_a are subnational (admin) level fixed effects and Z_{ct} are country $\times$ year FE; and e_{vct} are clustered at subnational (admin) level. In Panel A, access to health care is determined by the fraction of women who reported that distance was not an obstacle in the use of medical care; in panel B, antenatal care is defined as the fraction of average number of antenatal visits reported by women; in panel C: institutional delivery was defined as fraction of children who were reported to have been delivered in any kind of health facility; in panel D breastfeeding is calculated as the fraction of women who reported to be breastfeeding at the time of survey; and in panel E vaccination rates are calculated as the the fraction of children who received any vaccination (BCG, TB, DPT, Polio, Measles, etc.). The estimating sample is consists only of rural villages and the proportions are always calculating after restricting sample to mothers who reported to have never migrated.

Table 11: Association between area weighted MV and vaccination rates at the country level, 1980-2000

	(1) BCG	(2) DPT1	(3) DPT3	(4) MCV1	(5) PAB	(6) POL3
Area Weighted MV	51.9826 (54.3660)	26.7861 (43.6261)	57.9179 (39.3719)	94.6554 (28.2277)***	36.3919 (46.2926)	34.5495 (44.4590)
N	659	653	653	647	649	654

Note: Table 11 presents results for the following estimating equation: $y_{ct} = \gamma MV_{ct} + u_c + v_t + e_{ct}$ where, y_{vt} is the vaccination rate in country c in year t ; MV_{ct} is the area weighted MV; u_c are country fixed effects and v_t year FE; and e_{ct} are clustered at country level. Note: BCG refers to percentage of live births who received bacille Calmette-Guerin (vaccine against tuberculosis); DTP1 refers to percentage of surviving infants who received the first dose of DTP containing vaccine; DTP3 refers to percentage of surviving infants who received the first dose of DTP containing vaccine; MCV1 refers to percentage of surviving infants who received the first dose of measles containing vaccine; PAB refers to percentage of newborns protected at birth against tetanus and Pol3 refers to percentage of surviving infants who received the third dose of polio vaccine. The immunization data comes from UNICEF (Source: <https://data.unicef.org/topic/child-health/immunization/>).

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