# The Green Revolution and Rural Inequality: India

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December 4, 2023

A number of recent papers have found impressive, positive effects of the global Green Revolution on agricultural productivity and measures of average human welfare. Working with datasets that span the Green Revolution in India, we show early evidence that the roll-out of high-yielding crop varieties (mostly rice and wheat) seems to have increased land inequality and inequality in rural income and rural, female educational attainment. This is is line with scattered, small-scale evidence collected by Indian economists in the 1970s and 1980s. We are also exploring the mechanisms behind these distributional impacts; this is early work, with more to follow, not to be cited or circulated.

Keywords: High yielding varieties, agricultural productivity, rural inequality, land, health

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## 1 Introduction

A number of recent papers have found impressive, positive effects of the global Green Revolution on agricultural productivity and measures of human welfare. For instance, the roll-out of high-yielding varieties (HYVs) and modern inputs in poor countries increased cereal yields (Evenson and Gollin, 2003; Gollin, Hansen, and Wingender, 2018; McArthur and McCord, 2017), consequently lowering cereal prices (Evenson and Gollin, 2003). Adoption of HYVs decreased both adult and infant mortality but also decreased fertility rates, resulting in overall smaller populations (Gollin, Hansen, and Wingender, 2018; von der Goltz et al., 2020). Furthermore, on a global scale HYVs and increased fertilizer application appear to have reduced labor share to agriculture, increased per capita Gross Domestic Product, and — after a decade's lag — increased labor productivity in the non-agricultural sector (Gollin, Hansen, and Wingender, 2018; McArthur and McCord, 2017).

Yet these papers pay little heed to the distributional effects of the Green Revolution. In India particularly this seems like a yawning gap of inquiry, given that a great number of economists writing during the Indian Green Revolution itself expressed concern about its implications for rural inequality. For instance, many were concerned that small and "marginal" farmers were failing to adopt HYVs at the rate that larger farmers were, were less successful at growing HYVs, and/or were forced to take out unacceptable quantities of credit to finance HYV adoption (Dasgupta, 1977; Bhalla and Chadha, 1982a,b; Dhanagare, 1987). Others wrote that due to increasing land productivity and land prices, landlords were attempting to convert tenants and sharecroppers to hired, landless laborers – eroding the feasibility of ongoing, state-level land reform (Cleaver, 1972; Ladejinsky, 1969). Meanwhile, limited evidence from small datasets suggested that despite HYVs requiring additional labor, real agricultural wages may have stagnated in the 1960s and 1970s (perhaps due to increased labor supply or to spurred mechanization), making landless laborers worse off than ever (Bardhan, 1970; Cleaver, 1972; Dasgupta, 1977; Dhanagare, 1987). A number of Indian economists ultimately suggested that HYVs drove increased skewness in the distribution of agricultural land, farming assets, or even income itself in rural India (Dasgupta, 1977; Junakar, 1975; Bardhan, 1970; Dhanagare, 1987; Bhalla and Chadha, 1982b).

We provide the first empirical investigation of the distributional consequences of the Green Revolution, working in the context of India, the poster child for the revolution. We use district-level, household-level, and individual-level data stretching from the 1960s-2000, and quasi-experimental variation in the within-state roll-out of HYVs to provide causal identification (Bharadwaj et al., 2020). We find that HYV roll-out increased land inequality by increasing acreage to marginal and larger farmers, and decreasing acreage to medium-sized farmers. HYV roll-out also increased inequality in rural income per capita and in female educational attainment. In ongoing work, we examine the mechanisms behind these distributive impacts.

Very few studies explicitly examine the impact of improved agricultural productivity on rural inequality, despite the accepted importance of both agricultural productivity and inequality for economic growth (e.g., Gollin, Parente, and Rogerson (2002), Alesina and Rodrik (1994)). However, it is well known that in smallholder contexts, new agricultural technologies often differentially benefit the richest or largest farmers (Goldstein and Udry, 2008; Foster and Rosenzweig, 2010; Heß, Jaimovich, and Schündeln, 2021), with obvious implications for inequality among the landed. New agricultural technologies may also impact agricultural wages — driving them down if labor-savings, up if labor-demanding — with direct implications for agricultural laborers and inequality and further impacts on local non-agricultural sector growth (Bustos, Caprettini, and Ponticelli, 2016; Foster and Rosenzweig, 2004). Increased agricultural productivity may also influence decisions around extended family structure and land division practices (Foster and Rosenzweig, 2002; Bardhan et al., 2014), again with implications for rural inequality.

A few papers hint at distributive impacts of the Indian Green Revolution in particular, though again without directly exploring them. Bardhan and Mookherjee (2011) find that government-subsidized HYV seeds and input kits were equally profitable for small and large farmers during the 1980s and 1990s in West Bengal<sup>1</sup>, while using a nationally representative dataset from 1968-1971, Foster and Rosenzweig (1996) find that only educated Indian farmers with large farms profited from HYVs. In a working paper, D'Agostino (2017) finds that HYV wheat roll-out predicted increased male wages but decreased female wages. Bharadwaj et al. (2020) finds that HYVs reduced child mortality most for rural mothers, poor mothers, and mothers from marginalized castes, implying a mitigating effect on rural health inequality. And of course, a number of papers written during the Green Revolution in India directly speculate about the distributive impacts of these new crops, but without the data necessary to robustly address the question.

We therefore provide three contributions. We contribute to the literature on agricultural productivity and economic development by examining the effect of increased agricultural productivity on rural inequality – a mediator of growth and structural change – in India. We also contribute to the economics literature on the impacts of the Green Revolution (Evenson and Gollin, 2003; Gollin, Hansen, and Wingender, 2018), being the first paper that we know of to directly examine distributive impacts and the mechanisms behind those impacts. The mechanisms we examine include both demographic and labor market channels. Finally, we contribute context to literature on redistributive land policies (Besley and Burgess, 2000), as increased agricultural productivity during the Green Revolution seems to have increased incentive to aggregate land and therefore to use inheritance practices to thwart the land reform policies being rolled out by Indian states in the 1960s and '70s. Our results are not, however, driven by correlation between HYV roll-out and land reform, since land reform was legislated and enacted by states (Besley and Burgess, 2000), and our econometric specifications leverage district-level variation, holding state-year fixed effects constant.

Our findings are also relevant for sub-Saharan Africa as governments, research institutes and foundations attempt to bring a "Green Revolution 2.0" to sub-Saharan Africa (Blaustein, 2008; Diao, Headey, and Johnson, 2008; Dawson, Martin, and Sikor, 2016; Gassner et al., 2019). In 2006, the Bill and Melinda Gates Foundation joined the Rockefeller Foundation to create the Alliance for a Green Revolution in Africa (AGRA). AGRA hopes to "catalyze an inclusive agricultural transformation in Africa" through

 $<sup>^1\</sup>mathrm{They}$  also find that the kits increased demand for a gricultural workers and had no impact on worker wages.

improving crop varieties, improving agronomic conditions (e.g., soil fertility, irrigation), and improving farmer access to markets, to name a few strategic focuses (Blaustein, 2008). In remarks at the 2007 World Economic Forum, former UN Secretary General Kofi Annan noted, "AGRA is answering the call of many African leaders to build on the achievements and lessons learned from the Green Revolution in Asia and Latin America that began more than a generation ago. That campaign – initiated by the Rockefeller Foundation – saved hundreds of millions of lives and more than doubled cereal production." We hope that by further probing the distributional impacts of the Green Revolution in India, we may provide insights useful for new agricultural policy in Africa as well as in Asia.

### 2 Data

We use district-level data on agricultural conditions from the district-level Village Dynamics in South Asia (VDSA) panel collected by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The VDSA panel covers 311 districts across nineteen states of India over the period 1966 to 2011, tracking the 1966 districts even after they've divided by apportioning data from subsequently-created districts back to their 1966 "parent districts". The VDSA holds information on cropping patterns, input use, area under high yielding varieties, irrigated area, etc. It also holds the number of marginal (< 1ha), small (1-2 ha), semi-medium (2-4 ha), medium (4-10 ha) and large (>10 ha) farms in each district and year, and the land area devoted to each of those farm categories. It is important that the VDSA begins in 1966, the year that HYVs were introduced to India. For a few robustness checks we may also use the district-level Indian Agriculture and Climate Dataset (IACD) panel, which is similar to the VDSA dataset but begins in 1956. The IACD data were collected by India's Ministry of Agriculture in partnership with the World Bank, and covers 271 districts across thirteen states of India.

During the period that we examine, 1966-2000, the area under high-yielding crop varieties grew dramatically (Figure 1). This was particularly true in districts with better access to groundwater. However, the quality of VDSA data on high-yielding variety coverage also degrades in many districts after 1989 (Figure 1), making it difficult to examine the impacts of, or even associations with, HYVs in this final decade of the Green Revolution. When working with VDSA data in this final decade we therefore employ multiple robustness checks, e.g. limiting analysis to districts that seem to have trustable data, using aquifer-predicted trends in HYVs, or aggregating farm-level acreage to proxy for district-level coverage. During the same time period number of marginal and small farmers in India grew dramatically, while the number of medium-sized and large farmers shrank. The proportion of agricultural land under each farmer category moved accordingly (Figure 2)

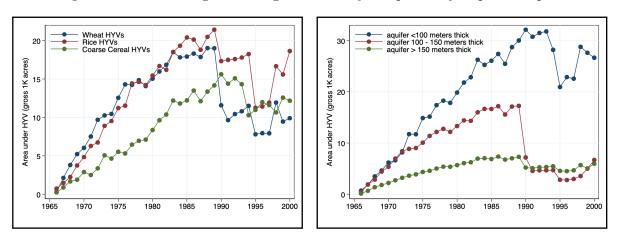


Figure 1: Area to High-Yielding Varieties by Crop and by Aquifer Depth

Each point represents total area recorded under high-yielding varieties within the given category. The drops in apparent coverage post-1989 are primarily driven by missing (district-level) data. Some districts also record reduced coverage in the 1990s, likely reflecting flagging adherence to comprehensive recording.

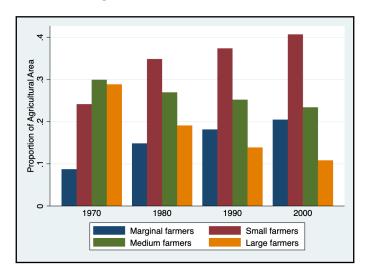


Figure 2: Change in Farm Area Distribution Over Time

Marginal farms have < 1 ha of land, small farms have 1-4 ha, medium farms have 4-10 ha, and large farms have > 10 ha.

We use the household-level ARIS-REDS data to examine individual farmer choices, profits, inputs and assets, etc. The first wave of the Additional Rural Incomes Survey (ARIS) data was collected by the National Council for Applied Economic Research in 1971. It includes 4527 households residing in 17 major states and 100 districts of the country. Sampling was conducted such that the dataset was representative of the entire rural population of India, with an oversampling of wealthier households. In the 1981 Rural Economic and Demographic (REDS) surveys, 4979 households were surveyed, approximately two-thirds of which were the same as ARIS households in 1971. In 1999, all the surviving households of 1981 survey were surveyed again, including all split-off households. Using data on the original 1971 households only, we construct a 1971-1999 panel, the only household-level panel dataset in India that spans the Green Revolution

and focuses on agriculture. We also use the newly- sampled households in 1982 and 1999 to create a pooled cross-sectional dataset. We can also examine intergenerational land transfers using the split-off households interviewed in 1999. Like the 2009-14 data used by Foster and Rosenzweig (2022), the ARIS-REDS datasets over-sample high- and middle-income farmers, and therefore farmers with medium-sized and large farms. This allows us to examine change in productivity patterns over land size over time, and to ask whether high-yielding variety adoption drove those changes.

Finally, we pool individual-level maternal height data from two rounds of the National Family Health Survey (NFHS) conducted in 1998-1999 and 2015-2016. The NFHS are nationally representative household surveys that are primarily canvassed on a sample of females, aged between 15 to 49 years. These surveys collect detailed information on fertility, mortality, nutrition, health behavior and various household characteristics. The sample sizes in the two NFHS are different, but we pool them in order to get cohort years for both the pre- and post-green revolution period.<sup>2</sup> The final dataset includes information on mothers born between 1950 and 2000.

Using the NFHS, we will examine the effect of HYV roll-out on maternal height and stunting, and on the distribution of maternal height. While weight outcomes (such as BMI) reflect short-term health and nutritional status, adult height reflects cumulative net health, nutrition, and deprivation (Perkins et al., 2008). Height is therefore a measure of adult health stock. Maternal height is particularly important in India, as it is associated with child mortality, morbidity, and stunting (Subramanian et al., 2009).

## 3 Identifying Distributional Outcomes

High yielding varieties did not roll out randomly across India. For instance, HYVs were introduced first in Punjab and Haryana, where irrigation and mechanization were relatively widespread, farmers were relatively prosperous with larger land sizes, and due to recent land reform, farms were often being worked by their owners rather than by tenants (Dasgupta, 1977). As time went on, HYVs rolled out in less prosperous states, with less prevalent irrigation, mechanization, or even electrification.

So to examine the causal effect of HYVs in India, we must identify a form of plausible exogenous variation in roll-out. Following Bharadwaj et al. (2020), we assert that despite non-randomness in HYV roll-out across states, district-level variation in HYV prevalence within a state time period is plausible exogenous. That is, a district may be just ahead of its state's HYV trajectory during one period, or just behind it in another, for no particular reason – or for reasons that are unrelated to the outcomes of interest.

We examine this claim empirically in Table A1. Conditional on district and state-year fixed effects, concurrent and recent rainfall and temperature shocks do predict HYV prevalence: in most time periods, HYVs tend to be slightly more prevalent in districts that had a wetter or a cooler year. Yet socioeconomic characteristics such as population

<sup>&</sup>lt;sup>2</sup>We will control for differences in sample sizes and sampling procedure across the two NFHS by adding a survey dummy in all specifications, and also by running robustness checks with only the later, larger sample. We will also demonstrate the robustness of our results to differences in sampling procedures by estimating equation with and without NFHS sampling weights.

density, urbanization, literacy rates, or gender ratios in literacy do not predict HYV prevalence during any short time period (Columns 1-3) or during the entire period of 1966 to 2000 (Column 4).

To examine the plausibly causal impact of HYV roll-out in India, therefore, we model district-level outcomes  $Y_{dt}$  on the lagged proportion of gross cultivated area under HYVs in district d,  $HYV_{dt-k}$ , alongside district fixed effects  $\delta_d$ , state-year fixed effects  $\delta_{st}$ , and district-level lagged rainfall and temperature shocks,  $X_{dt-k}$ , since these shocks are correlated with HYV prevalence (Table A1). We generally lag HYV prevalence by 1 year (k = 1), but when appropriate to the outcome we show robustness to greater lags.<sup>3</sup>

$$Y_{dt} = \phi_0 + \phi_1 H Y V_{dt-k} + \phi_2 X_{dt-k} + \delta_d + \delta_{st} + \epsilon_{dt} \tag{1}$$

We first use Equation 1 to examine the impact of HYV roll-out on district-level farm land distribution, by setting  $Y_{dt}$  to the percent of farm land in district d in year t held by marginal, small, medium-sized, and large farms, respectively. This can be done using the VDSA data (where these district-level figures are viewed directly), or the ARIS-REDS data (where we can calculate the percent of surveyed farmland held by marginal, small, medium-sized, and large farms in each survey wave in each district, and also view the percent of rural households who are landless).

As a robustness check on these distributional findings, we follow Sekhri and Shastry (2019) to examine how landholding patterns changed differentially over time in water-rich vs. water-scarce districts, since water availability was a primary predictor of HYV take-up (Figure 1). We do this by estimating Equation 2 in the VDSA data, where each  $\zeta_1^t$  provides a year-specific change in the marginal effect of having thicker aquifers ( $A_d = 1$ ),<sup>4</sup> vis-a-vis the (unidentified) marginal effect in 1970.

$$Y_{dt} = \zeta_0 + \Sigma_t \zeta_1^t A_d * t + \zeta_2 X_{dt-1} + \delta_d + \delta_t + \upsilon_{dt}$$

$$\tag{2}$$

Ideally we would view land distribution prior to the start of the Green Revolution in 1968, to check for parallel pre-trends. However, we do not have land distribution data prior to 1970, and therefore view Equation 2 as a robustness check rather than an independent identification strategy. If HYV roll-out increases rural land inequality, we would expect the marginal effect of district aquifer thickness to be increasing for marginal and/or large farmers (i.e.,  $\zeta_1^t$  growing more positive over time) and decreasing for medium-sized farmers (i.e.,  $\zeta_1^t$  becoming more negative over time).

Because Rao, Eberhard, and Bharadwaj (2022) find that current-day rural land inequality in India is higher closer to towns, we re-estimate Equation 1 in sub-samples of the ARIS-REDS data according to 1971 distance to town, and 1971 distance to bus station (i.e., accessibility to towns). (This is not possible in the district-level VDSA data.) If HYVs primarily drive rural land inequality in villages with access to town, this could suggest a role for sectoral transition – e.g., medium-sized farms near to towns chose to sell land and turn to non-agricultural work after HYV roll-out increased land prices, in line with hypotheses by Rao, Eberhard, and Bharadwaj (2022).

<sup>&</sup>lt;sup>3</sup>When k = 1,  $X_{dt-k}$  holds rainfall and temperature shocks lagged 1 year, 2 years and 3 years. Relative to  $HYV_{dt-k}$ , this is concurrent rainfall and temperature shocks plus two lags, as held in Table A1. <sup>4</sup>Specifically, having aquifers  $\geq 100$  meters, according to the Indian Agriculture and Climate Dataset.

Next, we use Equation 1 to examine the impact of HYV roll-out on rural welfare distributions. We examine income distributions by setting  $Y_{dt}$  to the percent of ARIS-REDS farmers in district d in survey year t falling in the 1st, 2nd, 3rd, or 4th income quartile. We examine human capital distributions by setting  $Y_{dt}$  to the percent of NFHS women in any given district falling in the 1st, 2nd, 3rd, or 4th height quartile, or the 1st, 2nd, 3rd, or 4th education quartile.

When examining human capital distributions, we are interested in the effect of HYV prevalence in the year of a woman's birth. That is, we define t not as the year of survey, but as the year of birth. Adult height is a widely accepted proxy for early childhood health (Bevis and Villa, 2022). Adult education levels are shaped by early childhood health and early parental inputs, the latter often being shaped by perceptions of the long-term value of education and/or by the need for child labor (Foster and Rosenzweig, 1996, 2001). So, HYV prevalence in the year of birth might impact these two forms of human capital accumulation by shaping parental income and health/education inputs, by changing food availability patterns and early childhood nutrition, by influencing parent perceptions of the value of education or the family's need for agricultural labor, or through other pathways. We remain agnostic as to the particular pathway of impact.

## 4 Distributional Results

### 4.1 Farmland

Table 1 displays the impact of HYV roll-out on rural land distribution – that is, the results of estimating Equation 1 in the VDSA data, with  $Y_{dt}$  measuring the share of gross agricultural land in district d and year t held by marginal, small, medium-sized, and large farmers in turn. As HYVs roll-out within a state, the center of the land distribution hollows out (columns 2, 3) and the proportion of land held by the largest and the smallest farmers increases (columns 1, 4). More specifically, a 10 percentage point increase in the acreage of agricultural land allocated to HYV crops increases the acreage of agricultural land held by marginal (< 1 ha) farms and large (> 10 ha) farms by about half a percentage point each, and decreases acreage held by small (1-4 ha) and medium-sized (4-10 ha) farms by roughly that same amount.

This "hollowing out" effect is likely to be fairly constant across time. We do observe a stronger effect in the 1970-1980 sample alone, and a weaker effect when re-estimating in the 1985-2000 sample (Table A2). However, HYV roll-out retains much less variation after period-specific district fixed effects in 1985-2000, and so lack of identifying variation may be driving those weaker results.<sup>5</sup> When Equation 1 is re-estimated using data from 1970-1986, 1970-1990, and 1970-1995 (Table A3), we find that results vary little from that seen for 1970-1980 or for the entire 1970-2000 sample. This is likely because when extending the sample rather than splitting it, fixed effects still provide a longer-period mean, and thus adequate identifying variation in HYV roll-out remains.

<sup>&</sup>lt;sup>5</sup>Sixty-two percent of lagged HYV roll-out is explained by district fixed effects in the 1970-1980 sample, while 81% is in the 1985-2000 sample.

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
HYV_t-1	$\begin{array}{c} 0.0524^{***} \\ (0.0103) \end{array}$	$-0.0637^{***}$ (0.0235)	$-0.0514^{***}$ (0.0163)	$\begin{array}{c} 0.0626^{***} \\ (0.0212) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1549	1549	1549	1549
Within R <sup>2</sup>	0.0335	0.0271	0.0347	0.0358

 Table 1: Farmland Distribution (VDSA)

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

The effects seen in Table 1 are more generally robust. Results are similar if we examine the roll-out of wheat HYVs and rice HYVs alone, though rice HYVs have a larger and more significant inequality impact (Tables A4, A5). The hollowing out effect exists in districts with both thinner and thicker aquifers (Table A6). Effect sizes are virtually identical if we examine concurrent HYV prevalence or HYV prevalence lagged by 5 years, rather than by 1 year (Tables A7, A8). Importantly, measurement error in HYV acreage in the 1990-2000 data does not drive our results; the hollowing out effect shows up in the earlier data alone (Table A3), and dropping districts with more missing 1990-2000 data or more apparently errored 1990-2000 values intensifies the pattern (Tables A9, A10). It therefore seems that measurement error in HYV roll-out is biasing these treatment effects towards zero, as it would if classical.

	% Families	% Area to	% Area to	% Area to	% Area to
	Landless	Marginal Farms	Small Farms	Medium Farms	Large Farms
HYV_t-1	-0.0136 (0.103)	0.0277 (0.0418)	$\begin{array}{c} 0.194^{**} \\ (0.0840) \end{array}$	$-0.326^{**}$ (0.134)	$0.105 \\ (0.164)$
District FE	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	256	256	256	256	256
Within $\mathbb{R}^2$	0.0193	0.0826	0.101	0.0778	0.0234

 Table 2: Farmland Distribution (ARIS-REDS)

Outcomes: Proportion operational land-holdings held by each farmer category, within the ARIS-REDS panel (1971 households and their splits). Treatment: Proportion gross cultivated district area under HYVs, lagged one year. Sample: ARIS-REDS 1971 households and their split-offs. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

We observe a similar hollowing out effect in the ARIS-REDS dataset, though with a reduction in medium-sized farms only. Table 2 holds the results of estimating Equation 1 using the ARIS-REDS panel of 1971 households and those who split from the panel households. In this case,  $Y_{dt}$  reflects the percent of *surveyed* land being held by marginal, small, medium-sized or large farmers. A 10 percentage point increase in district-level acreage to HYV crops reduces the percent of surveyed land held by medium-sized' farmers by 3 percentage points, and increases the percent of surveyed land held by small farmers by 2 percentage points. We observe no significant effect on the percent of farmland held by marginal or large farmers, though the directions of impact are in line with the VDSA results.

As a methodological check on these distributional findings, we estimate Equation 2 in the VDSA data to examine how landholding patterns changed differentially over time in water-rich vs. water-scarce districts. Figure 3 holds the results: the marginal effect of district-level aquifer thickness increases over time for marginal and large farmers, and decreases over time for small and medium-sized farmers. This is precisely what we would expect to find if being water-rich drove increased, district-level HYV prevalence over time, and if district-level HYV prevalence drove rural inequality.

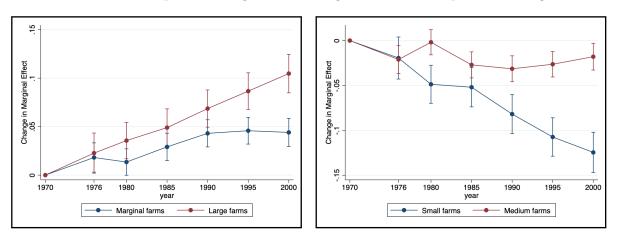


Figure 3: Temporal Change in the Marginal Effect of Aquifer Coverage

Last, we examine whether the impact of HYVs on rural land distribution varies with proximity to towns or public transportation by re-estimating Equation 1 in ARIS-RED sub-samples.<sup>6</sup> The impacts of HYV roll-out on land inequality does not vary by 1971 proximity to towns (Table A11). However, HYV roll-out does have a stronger impact on land inequality in the villages that were within 5 km of a bus stop in 1971 (Table A12), with very little impact in the villages that started out with poor transportation options.

#### 4.2 Rural welfare

Using the ARIS-REDS data, we find that the impact of HYVs on the per capita income distribution mirrors the impact of HYVs on the farmland distribution (Table 3). An increase in district-level HYV prevalence increases the proportion of households at the top and bottom of the income distribution, while decreasing the proportion of households in the middle. The negative coefficient for quartile 3 is the most statistically significant and the most robust to changes in specification (e.g., a similar farmer-level regression finds the effect for quartile 1 insignificant but that for quartile 4 significant).

<sup>&</sup>lt;sup>6</sup>That is, we drop sub-samples based on village-level proximity to towns or bus stops, then aggregate the remaining observations to calculate the percent of surveyed agricultural land held by each farmer category and the percent of surveyed households that are landless.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HYV_t-1	$0.261^{*}$ (0.139)	-0.0802 (0.0970)	$-0.353^{***}$ (0.0961)	$\begin{array}{c} 0.155 \ (0.109) \end{array}$
District FE State-Year FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes
$\begin{array}{c} \text{Observations} \\ \text{Within } \mathbf{R}^2 \end{array}$	$256 \\ 0.0695$	$256 \\ 0.0489$	$256 \\ 0.0855$	$256 \\ 0.0661$

**Table 3:** Per Capita Income Distribution (ARIS-REDS)

Outcomes: District-level percent of farmers falling in the 1st, 2nd, 3rd, or 4th per capita income quartile. Treatment: Proportion gross cultivated district area under HYVs, lagged one year. Sample: ARIS-REDS 1971 households and their split-offs. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

Using the NFHS data, we find that HYV roll-out in the year prior to birth has an overall positive effect on women's height (Table 4), and thus presumably on early childhood health during the Green Revolution. As district-level HYV prevalence increases, less women fall into the lower two height quartiles and more women fall into the upper height quartiles. An individual-level regression finds that a twenty-five percentage point increase in HYV prevalence at birth (achieved in half of districts by 1985) increases rural women's height by approximately 0.9 cm at the mean of the distribution (Table A13). For context, the mean difference in height between (better-off) Hindu and (worse-off) Muslim women in India is 0.1 cm.

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HYV_t-1	-0.0136 (0.0187)	-0.00718 (0.0185)	$0.00184 \\ (0.0174)$	$0.0191 \\ (0.0259)$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations Within $\mathbb{R}^2$	$\frac{13892}{0.000656}$	$\frac{13892}{0.000423}$	$\frac{13892}{0.000989}$	$\frac{13892}{0.000370}$

 Table 4: Height Distribution (NFHS)

Outcomes: District-level percent of women falling in the 1st, 2nd, 3rd, or 4th height quartile, for any given year of birth. Treatment: Proportion gross cultivated district area under HYVs, lagged one year before birth. Sample: 1998 and 2015 NFHS samples. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

A similar, individual-level regression finds that a ten percentage point increase in HYV prevalence at birth increases rural women's educational attainment by 3/4 of a year, at the mean (Table A13). However, this improvement in educational attainment is not uniform; HYVs again increase the proportion of women who fall in the upper and lower tails of the height distribution, while decreasing the proportion of women who fall in the positive (though insignificant) coefficient for quartile 1 indicates that as HYVs roll out, *more* women receive zero education. Even if this effect was null, the improvement in education would be occurring only at the top of the distribution. A similar but slightly different break-down of educational categories indicates that HYV roll-out decreases the proportion of women with only primary or secondary education, while increasing the proportion of women with no education or with higher education (Table A14).

	Quartile 1	Quartile 2	Quartile 3	Quartile 4
HYV_t-1	$\begin{array}{c} 0.0451 \\ (0.0324) \end{array}$	$-0.0672^{***}$ (0.0225)	$-0.0461^{**}$ (0.0227)	$\begin{array}{c} 0.0685^{***} \\ (0.0247) \end{array}$
District FE State-Year FE Observations Within R <sup>2</sup>	Yes Yes 13892 0.00105	Yes Yes 13892 0.00275	Yes Yes 13892 0.00100	Yes Yes 13892 0.00317

 Table 5: Education Distribution (NFHS)

Outcomes: District-level percent of women falling in the 1st, 2nd, 3rd, or 4th years-of-education quartile. Treatment: Proportion gross cultivated district area under HYVs, lagged one year before birth. Sample: 1998 and 2015 NFHS samples. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### 5 Model and Mechanisms

In ongoing work, we are using the VDSA and the ARIS-REDS dataset to investigate the mechanisms behind the distributional results shown in Section 4. This work continues to use plausibly exogenous variation in the district-level roll-out of HYVs to achieve causal identification.

In preliminary results we find, for instance, that larger farmers are more likely to adopt HYVs. Conditional on adoption profits appear close to scale-neutral, but smaller farmers who adopt HYVs see a rise in their costs per hectare (whereas larger farmers see a decline), leading HYVs to be riskier for smaller farmers than for larger farmers. District-level HYV roll-out leads to rising land prices and more land sales. It also decreases both household and land division, likely because operation on larger land sizes is less risky.

### References

- Alesina, A., and D. Rodrik. 1994. "Distributive politics and economic growth." *The quarterly journal of economics* 109:465–490.
- Bardhan, P. 1970. "Green Revolution'and Agricultural Labourers." *Economic and Political Weekly*, pp. 1239–1246.
- Bardhan, P., M. Luca, D. Mookherjee, and F. Pino. 2014. "Evolution of land distribution in West Bengal 1967–2004: Role of land reform and demographic changes." *Journal of Development Economics* 110:171–190.
- Bardhan, P., and D. Mookherjee. 2011. "Subsidized farm input programs and agricultural performance: A farm-level analysis of West Bengal's green revolution, 1982-1995." *American Economic Journal: Applied Economics* 3:186–214.
- Besley, T., and R. Burgess. 2000. "Land reform, poverty reduction, and growth: Evidence from India." *The Quarterly Journal of Economics* 115:389–430.
- Bevis, L.E., and K. Villa. 2022. "Intergenerational Transmission of Maternal Health Evidence from Cebu, the Philippines." *Journal of Human Resources* 57:1425–1465.
- Bhalla, G., and G. Chadha. 1982a. "Green Revolution and the Small Peasant: A Study of Income Distribution in Punjab Agriculture: I." *Economic and Political Weekly*, pp. 826–833.
- —. 1982b. "Green Revolution and the Small Peasant: A Study of Income Distribution in Punjab Agriculture: II." *Economic and Political Weekly*, pp. 870–877.
- Bharadwaj, P., J. Fenske, N. Kala, and R.A. Mirza. 2020. "The Green revolution and infant mortality in India." *Journal of health economics* 71:102314.
- Blaustein, R.J. 2008. "The green revolution arrives in Africa." *Bioscience* 58:8–14.
- Bustos, P., B. Caprettini, and J. Ponticelli. 2016. "Agricultural productivity and structural transformation: Evidence from Brazil." *American Economic Review* 106:1320–1365.
- Cleaver, H.M. 1972. "The contradictions of the Green Revolution." *The American* economic review 62:177–186.
- D'Agostino, A. 2017. "Technical change and gender wage inequality: long-run effects of India's green revolution." Available at SSRN 3400889, pp. .
- Dasgupta, B. 1977. "India's green revolution." *Economic and political weekly*, pp. 241–260.
- Dawson, N., A. Martin, and T. Sikor. 2016. "Green revolution in sub-Saharan Africa: implications of imposed innovation for the wellbeing of rural smallholders." World Development 78:204–218.
- Dhanagare, D.N. 1987. "Green revolution and social inequalities in rural India." *Economic and political weekly*, pp. AN137–AN144.

- Diao, X., D. Headey, and M. Johnson. 2008. "Toward a green revolution in Africa: what would it achieve, and what would it require?" *Agricultural Economics* 39:539–550.
- Evenson, R.E., and D. Gollin. 2003. "Assessing the impact of the Green Revolution, 1960 to 2000." science 300:758–762.
- Foster, A.D., and M.R. Rosenzweig. 2004. "Agricultural productivity growth, rural economic diversity, and economic reforms: India, 1970–2000." *Economic Development and Cultural Change* 52:509–542.
- —. 2022. "Are there too many farms in the world? labor market transaction costs, machine capacities, and optimal farm size." *Journal of Political Economy* 130:636–680.
- —. 2001. "Consequences of the Green Revolution for rural landless households: The complex relationship between income growth and human development." *Brown University, Providence, RI, USA Photocopy*, pp. .
- —. 2002. "Household division and rural economic growth." *The Review of Economic Studies* 69:839–869.
- —. 2010. "Microeconomics of technology adoption." Annu. Rev. Econ. 2:395–424.
- —. 1996. "Technical change and human-capital returns and investments: evidence from the green revolution." *The American economic review*, pp. 931–953.
- Gassner, A., D. Harris, K. Mausch, A. Terheggen, C. Lopes, R. Finlayson, and P. Dobie. 2019. "Poverty eradication and food security through agriculture in Africa: Rethinking objectives and entry points." *Outlook on Agriculture* 48:309–315.
- Goldstein, M., and C. Udry. 2008. "The profits of power: Land rights and agricultural investment in Ghana." *Journal of political Economy* 116:981–1022.
- Gollin, D., C.W. Hansen, and A. Wingender. 2018. "Two blades of grass: The impact of the green revolution." Working paper, National Bureau of Economic Research.
- Gollin, D., S. Parente, and R. Rogerson. 2002. "The role of agriculture in development." *American economic review* 92:160–164.
- Heß, S., D. Jaimovich, and M. Schündeln. 2021. "Development projects and economic networks: Lessons from rural gambia." The Review of Economic Studies 88:1347–1384.
- Junakar, P.N.R. 1975. Development Economics The Role of Agriculture in Development. Palgrave Macmilan.
- Ladejinsky, W. 1969. "Ironies of India's green revolution." Foreign Aff. 48:758.
- McArthur, J.W., and G.C. McCord. 2017. "Fertilizing growth: Agricultural inputs and their effects in economic development." *Journal of development economics* 127:133–152.
- Perkins, J.N., S.V. Subramanian, G.D. Smith, and E. Ozaltin. 2008. "Height, health, and income in the US, 1984–2005." *Economics and Human Biology* 6:108—126.

- Rao, M., J. Eberhard, and P. Bharadwaj. 2022. "Towns and Rural Land Inequality in India.", pp. .
- Sekhri, S., and G. Shastry. 2019. "The curse of plenty: Early Childhood roots of the rise in chronic disease." Working paper, Tech. rep., Working Paper, University of Virginia.
- Subramanian, S., L.K. Ackerson, G.D. Smith, and N.A. John. 2009. "Association of maternal height with child mortality, anthropometric failure, and anemia in India." Jama 301:1691–1701.
- von der Goltz, J., A. Dar, R. Fishman, N.D. Mueller, P. Barnwal, and G.C. McCord. 2020. "Health impacts of the green revolution: Evidence from 600,000 births across the developing world." *Journal of health economics* 74:102373.

# Appendix A Additional Figures and Results

	(1) 1966-1971	(2) 1972-1981	(3) 1982-2000	
Rainfall this year (cv mm)	$\begin{array}{c} 0.00555^{**} \\ (0.00215) \end{array}$	$\begin{array}{c} 0.00309^{***} \\ (0.00116) \end{array}$	$\begin{array}{c} 0.00396^{**} \\ (0.00171) \end{array}$	$\begin{array}{c} 0.00400^{***} \\ (0.00119) \end{array}$
Rain last year (cv mm)	$\begin{array}{c} 0.00463^{**} \\ (0.00228) \end{array}$	$\begin{array}{c} -0.000419 \\ (0.00114) \end{array}$	0.00151 (0.00156)	$0.00143 \\ (0.00106)$
Rain two years ago (cv mm)	$0.00597^{**}$ (0.00241)	-0.000983 (0.00108)	$\begin{array}{c} -0.000261 \\ (0.00170) \end{array}$	$\begin{array}{c} 0.000914 \\ (0.00111) \end{array}$
Temperature this year (cv C)	-0.00323 (0.00328)	$-0.00548^{**}$ (0.00227)	0.00387 (0.00361)	-0.00134 (0.00250)
Temperature last year (cv C)	-0.000693 $(0.00330)$	$0.00115 \\ (0.00212)$	-0.00181 (0.00296)	-0.00308 (0.00191)
Temperature two years ago (cv C)	-0.00173 (0.00274)	$0.00377^{*}$ (0.00209)	$-0.00594^{*}$ (0.00338)	$-0.00474^{**}$ (0.00232)
Population density (log person/hectare)	$\begin{array}{c} 0.00770 \ (0.0790) \end{array}$	-0.00925 (0.0143)	$\begin{array}{c} 0.0106 \ (0.0401) \end{array}$	-0.0354 (0.0324)
Urban population (% of total)	-0.380 (0.811)	-0.0500 (0.184)	$\begin{array}{c} 0.0821 \ (0.131) \end{array}$	$0.0224 \\ (0.107)$
Gender ratio (male:female)	$0.496^{*}$ (0.262)	-0.105 (0.333)	$\begin{array}{c} 0.557 \ (0.424) \end{array}$	$0.0800 \\ (0.219)$
Literacy rate (%)	$0.246 \\ (0.228)$	$0.0778 \\ (0.104)$	$\begin{array}{c} 0.199 \\ (0.177) \end{array}$	$0.248^{*}$ (0.128)
Literacy gender ratio (male:female)	$\begin{array}{c} 0.0387 \ (0.0350) \end{array}$	$\begin{array}{c} 0.0250 \\ (0.0186) \end{array}$	-0.0103 (0.0168)	-0.00672 (0.0114)
District Fixed Effects State-Year Fixed Effects	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Weather shock Fstat Prob > F Socioeconomic characteristic Fstat Prob > F	$\begin{array}{c} 2.330 \\ 0.0300 \\ 1.510 \\ 0.190 \end{array}$	$4.180 \\ 0 \\ 0.870 \\ 0.500$	$\begin{array}{c} 1.580 \\ 0.150 \\ 0.790 \\ 0.560 \end{array}$	$3.490 \\ 0 \\ 1.090 \\ 0.370$
Observations $R^2$	$1197 \\ 0.0323$	$\begin{array}{c} 2810\\ 0.0134\end{array}$	$4273 \\ 0.00954$	$8295 \\ 0.0116$

 Table A1: Is HYV Roll-Out Within States Exogenous? Suggestive Evidence

Outcome: Proportion gross cultivated area under HYVs. Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
<b>1970-1980 sample:</b> HYV_t-1	$0.0606^{***}$ (0.0203)	$-0.0641^{**}$ (0.0250)	$-0.0905^{***}$ (0.0228)	$\begin{array}{c} 0.0940^{***} \\ (0.0284) \end{array}$
$\begin{array}{c} Observations \\ R^2 \end{array}$	$\begin{array}{c} 604 \\ 0.0464 \end{array}$	$\begin{array}{c} 604 \\ 0.0496 \end{array}$	604 0.113	604 0.0947
<b>1985-2000 sample:</b> HYV_t-1	$0.0218^{**}$	-0.0491**	0.000570	$0.0267^{*}$
	(0.0108)	(0.0207)	(0.0140)	(0.0151)
Observations R <sup>2</sup>	867 0.0207	$\begin{array}{c} 867 \\ 0.0425 \end{array}$	$\begin{array}{c} 867 \\ 0.0316 \end{array}$	867 0.0123
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

 
 Table A2:
 Farm Area Distribution as HYVs Roll Out (VDSA Sample Split
 by Time Period)

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

Table A3:         Farm Area Distribution as HYVs Roll Out (VDSA Sample over
Varying Time Periods)

	% Area to Marginal Farms	% Area to Small Farms	% Area to Medium Farms	% Area to Large Farms
<b>1970-1986 sample:</b> HYV_t-1	$\begin{array}{c} 0.0430^{***} \\ (0.0129) \end{array}$	$-0.0381^{*}$ (0.0217)	$-0.0648^{***}$ (0.0170)	$0.0600^{**}$ (0.0250)
$\begin{array}{c} Observations \\ R^2 \end{array}$	919 0.0214	$\begin{array}{c} 919 \\ 0.0345 \end{array}$	$919 \\ 0.0518$	$919 \\ 0.0677$
<b>1970-1990 sample:</b> HYV_t-1	$\begin{array}{c} 0.0417^{***} \\ (0.0111) \end{array}$	$-0.0391^{*}$ (0.0209)	$-0.0449^{***}$ (0.0139)	$\begin{array}{c} 0.0424^{**} \\ (0.0212) \end{array}$
$\begin{array}{c} \text{Observations} \\ \text{R}^2 \end{array}$	$1163 \\ 0.0254$	$1163 \\ 0.0339$	$1163 \\ 0.0328$	$1163 \\ 0.0540$
<b>1970-1995 sample:</b> HYV_t-1	$\begin{array}{c} 0.0483^{***} \\ (0.0101) \end{array}$	$-0.0658^{***}$ (0.0226)	$-0.0466^{***}$ (0.0153)	$\begin{array}{c} 0.0642^{***} \\ (0.0202) \end{array}$
$\begin{array}{c} Observations \\ R^2 \end{array}$	$1356 \\ 0.0326$	$1356 \\ 0.0274$	$1356 \\ 0.0292$	$\begin{array}{c} 1356 \\ 0.0363 \end{array}$
District FE State-Year FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
Wheat HYV_t-1	$\begin{array}{c} 0.0704^{***} \\ (0.0196) \end{array}$	-0.0138 (0.0339)	$-0.0704^{*}$ (0.0380)	$0.0137 \\ (0.0369)$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1533	1533	1533	1533
Within $\mathbb{R}^2$	0.0142	0.0136	0.0244	0.0217

 Table A4:
 Farm Area Distribution as HYV-Wheat Rolled Out (VDSA)

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1

 Table A5:
 Farm Area Distribution as HYV-Rice Rolled Out (VDSA)

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
Rice HYV_t-1	$\begin{array}{c} 0.0650^{***} \\ (0.0153) \end{array}$	$-0.159^{***}$ (0.0328)	$-0.0597^{***}$ (0.0207)	$\begin{array}{c} 0.154^{***} \\ (0.0285) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1551	1551	1551	1551
Within R <sup>2</sup>	0.0318	0.0625	0.0317	0.0727

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A6:         Farm Area Distribution as HY	Vs Rolled Out, by	Aquifer Depth (	(VDSA)
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	% Area to Marginal Farms	% Area to Small Farms	% Area to Medium Farms	% Area to Large Farms
Aquifer < 100 m $\times$ HYV_t-1	$\begin{array}{c} 0.0503^{***} \\ (0.0112) \end{array}$	$-0.0560^{**}$ (0.0267)	$-0.0621^{***}$ (0.0182)	$\begin{array}{c} 0.0677^{***} \\ (0.0241) \end{array}$
Aquifer $\geq 100~{\rm m} \times {\rm HYV\_t-1}$	$\begin{array}{c} 0.0589^{***} \\ (0.0171) \end{array}$	$-0.0876^{***}$ (0.0274)	-0.0183 (0.0209)	$0.0470 \\ (0.0292)$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
$\begin{array}{l} \text{Observations} \\ \text{Within } \mathbf{R}^2 \end{array}$	$1549 \\ 0.0337$	$1549 \\ 0.0282$	$\begin{array}{c} 1549 \\ 0.0386 \end{array}$	$1549 \\ 0.0363$

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
HYV_t	$\begin{array}{c} 0.0551^{***} \\ (0.0105) \end{array}$	$-0.0725^{***}$ (0.0261)	$-0.0642^{***}$ (0.0180)	$\begin{array}{c} 0.0817^{***} \\ (0.0247) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1375	1375	1375	1375
Within R <sup>2</sup>	0.0372	0.0278	0.0449	0.0448

**Table A7:** Farm Area Distribution as HYVs Rolled Out, ConcurrentHYV Coverage (VDSA)

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A8:** Farm Area Distribution as HYVs Rolled Out, ConcurrentHYV Coverage (VDSA)

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
HYV_t-5	$\begin{array}{c} 0.0488^{***} \\ (0.0160) \end{array}$	$-0.0735^{***}$ (0.0251)	$-0.0513^{***}$ (0.0163)	$\begin{array}{c} 0.0760^{***} \\ (0.0220) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1530	1530	1530	1530
Within R <sup>2</sup>	0.0281	0.0359	0.0274	0.0463

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

**Table A9:** Farm Area Distribution as HYVs Roll Out (VDSA, dropping districts with > 5 missing HYV values in 1990-2000)

	% Area to	% Area to	% Area to	% Area to
	Marginal Farms	Small Farms	Medium Farms	Large Farms
HYV_t-1	$\begin{array}{c} 0.0467^{***} \\ (0.0107) \end{array}$	$-0.0610^{**}$ (0.0272)	$-0.0561^{***}$ (0.0188)	$\begin{array}{c} 0.0704^{***} \\ (0.0246) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	1296	1296	1296	1296
Within R <sup>2</sup>	0.0352	0.0282	0.0360	0.0427

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000 with  $\leq 5$  missing  $HYV_{t-1}$  values in the years 1990-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	% Area to Marginal Farms	% Area to Small Farms	% Area to Medium Farms	% Area to Large Farms
HYV_t-1	$\begin{array}{c} 0.0574^{***} \\ (0.0165) \end{array}$	$-0.0971^{**}$ (0.0375)	$-0.0820^{***}$ (0.0254)	$\begin{array}{c} 0.122^{***} \\ (0.0337) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	741	741	741	741
Within $\mathbb{R}^2$	0.0576	0.0581	0.0464	0.0803

Table A10: Farm Area Distribution as HYVs Roll Out (VDSA, dropping districts with > 5 missing HYV values or with unstable HYV values in in 1990-2000)

Outcomes: Proportion operational land-holdings held by each farmer category. Treatment: Proportion gross cultivated area under HYVs, lagged one year. Sample: VDSA districts 1966-2000 with  $\leq 5$  missing  $HYV_{t-1}$  values in the years 1990-2000, and no more than 2  $HYV_{t-1}$  values that change by more than 5% in a year during 1990-2000. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table A11: Farmland Distribution (ARIS-REDS, Split by Proximity to Town)

Villages $\leq$ 14km from town in 1971:	% Families Landless	% Area to Marginal Farms	% Area to Small Farms	% Area to Medium Farms	% Area to Large Farms
HYV_t-1	0.0914 (0.0955)	0.0274 (0.0517)	$0.204^{*}$ (0.108)	$-0.514^{***}$ (0.192)	$0.283 \\ (0.219)$
$\begin{array}{c} \text{Observations} \\ \text{Within } \mathbf{R}^2 \end{array}$	$\begin{array}{c} 191 \\ 0.116 \end{array}$	190 0.0810	$190 \\ 0.0759$	190 0.148	$\begin{array}{c} 190 \\ 0.0366 \end{array}$
Villages $\leq$ 14km from town in 1971:					
HYV_t-1	-0.0753 (0.167)	$0.00364 \\ (0.0195)$	$0.194^{*}$ (0.0994)	$-0.581^{***}$ (0.212)	$0.384 \\ (0.247)$

Outcomes: Proportion operational land-holdings held by each farmer category, within the ARIS-REDS panel (1971 households and their splits). Treatment: Proportion gross cultivated district area under HYVs, lagged one year. Sample: ARIS-REDS 1971 households and their split-offs if living in a village  $\leq 5$  km from a bus stop (Panel 1), or if living in a village > 5km from a bus stop (Panel 2). Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Villages $\leq$ 5km from bus stop in 1971:	% Families Landless	% Area to Marginal Farms	% Area to Small Farms	% Area to Medium Farms	% Area to Large Farms
HYV_t-1	$0.0939 \\ (0.131)$	$0.0197 \\ (0.0604)$	$0.369^{***}$ (0.116)	$-0.799^{***}$ (0.185)	$0.410^{*}$ (0.220)
Observations Within $\mathbb{R}^2$	$202 \\ 0.0477$	$\begin{array}{c} 200 \\ 0.0847 \end{array}$	$200 \\ 0.225$	200 0.209	$200 \\ 0.0869$
Villages $\leq$ 5km from bus stop in 1971:					
HYV_t-1	-0.131 (0.175)	-0.0728 (0.0496)	$0.141 \\ (0.151)$	-0.199 (0.216)	0.131 (0.232)
District FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes

Table A12: Farmland Distribution (ARIS-REDS, Split by Proximity to Bus Stop)

Outcomes: Proportion operational land-holdings held by each farmer category, within the ARIS-REDS panel (1971 households and their splits). Treatment: Proportion gross cultivated district area under HYVs, lagged one year. Sample: ARIS-REDS 1971 households and their split-offs if living in a village  $\leq 5$  km from a bus stop (Panel 1), or if living in a village > 5km from a bus stop (Panel 2). Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). Bootstrapped standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

	PC Income	Height	Education
HYV_t-1	$0.0410 \\ (0.249)$	$0.373^{*}$ (0.191)	$\begin{array}{c} 0.756^{***} \\ (0.266) \end{array}$
Observations R <sup>2</sup> District FE State-Year FE	10354 0.00265 Yes Yes	397302 0.0000298 Yes Yes	405838 0.000183 Yes Yes

Table A13: Mean Welfare Effects (ARIS-REDS, NFHS)

Outcomes: Per capita income (col 1), female height (col 2), female education (col 3). Treatment: Proportion gross cultivated district area under HYVs, lagged one year before income was measured (col 1) or one year before birth (cols 2, 3). Sample: ARIS-REDS 1971 households and their split-offs (col1), rural 1998 and 2015 NFHS samples, pooled (cols 2-3). Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

 Table A14:
 Education Distribution (NFHS)

	No	Primary	Secondary	Higher
	Education	Education	Education	Education
HYV_t-1	$\begin{array}{c} 0.0451 \\ (0.0324) \end{array}$	$-0.0673^{***}$ (0.0225)	-0.00898 (0.0260)	$\begin{array}{c} 0.0315^{**} \\ (0.0143) \end{array}$
District FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	13892	13892	13892	13892
Within $\mathbb{R}^2$	0.00105	0.00275	0.000506	0.00170

Outcomes: District-level percent of women achieving no education, primary education, secondary education, or higher education. Treatment: Proportion gross cultivated district area under HYVs, lagged one year before birth. Sample: 1998 and 2015 NFHS samples. Covariates: Rainfall and temperature shocks (lagged 1, 2, and 3 years). District-clustered standard errors in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1