Technological Innovations, Downside Risk, and the Modernization of Agriculture[†]

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We use a randomized experiment in India to show that improved technology enhances agricultural productivity by crowding in modern inputs and cultivation practices. Specifically, we show that a new rice variety that reduces downside risk by providing flood tolerance has positive effects on adoption of a more labor-intensive planting method, area cultivated, fertilizer usage, and credit utilization. We find that a large share of the expected gains from the technology comes from crowding in of other investments. Therefore, improved technologies that reduce risk by protecting production in bad years have the potential to increase agricultural productivity in normal years. (*JEL* O13, O33, Q14, Q15, Q16)

Productivity growth in the agricultural sector is recognized as an important driver of structural transformation and economic growth for poor countries (Gollin, Parente, and Rogerson 2002). At the same time, agricultural productivity has been hindered by the failure of farmers in developing countries to use high levels of modern inputs and to adopt improved agricultural practices. Fertilizer is an oft-cited example. African farmers use fertilizers at much lower rates than farmers in the rest of the world (World Bank 2007). Similarly, farmers in the lowest-productivity rice-producing states in Eastern India use less than one-half of the fertilizer of those in the higher-productivity states in the country.[1]

Several explanations for limited modern input use and the failure to adopt improved practices have arisen in the literature. These include procrastination and

[1] We used the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) district-level database for all of India to calculate fertilizer use per hectare and rice yield during 2007. The lowest productivity states producing a large amount of rice are Odisha, Jharkhand, Chattisgarh, and Assam. Fertilizer use per hectare varies from 73 to 110 kg per hectare in these states. In contrast, fertilizer use is over double and productivity is substantially higher in other rice-producing states such as West Bengal and Andhra Pradesh.

time-inconsistent preferences (Duflo, Kremer, and Robinson 2011), high transaction costs due to poor infrastructure (Suri 2011), lack of information and difficulties in learning (Ashraf, Giné, and Karlan 2009; Hanna, Mullainathan, and Schwartzstein 2014), and absence of formal insurance (Karlan et al. 2014). An additional plausible explanation—this time on the supply side of technology—is that smallholder farmers lack technologies that are well suited to local conditions and therefore factor deepening and adoption of other improved agricultural practices are not optimal. Put differently, can the availability of new technologies that are better suited to local conditions crowd in additional inputs and investments in other productivity-enhancing practices?

In this paper we answer this question by showing that technological innovation in agriculture can itself create a factor deepening effect where improved practices and additional inputs are used in response to innovation. Specifically, we study the dissemination of an innovative new rice variety that is well suited to local conditions in flood-prone areas because its key feature is flood tolerance. The technology reduces downside risk by decreasing crop damage during flooding, while at the same time leaving production unaffected during normal years.

Our experiment was carried out over two years in the eastern Indian state of Odisha. We randomized the distribution of a new rice variety called Swarna-Sub1 across 128 villages. This seed variety is nearly identical to Swarna, the popular high-yielding variety grown in this area, with the only difference being improved flood tolerance.[2] Prior to the 2011 wet season, a random subset of 5 farmers in each of 64 treatment villages were provided a small package of Swarna-Sub1 seed. This "minikit" contained only seeds and a short information sheet on the properties of Swarna-Sub1. The comparison farmers in the remaining villages were not provided with any seeds, as Swarna is widely grown in the area.

In general, our main finding is that this technological innovation leads to not only avoided yield losses under flooding but also significant factor deepening and adoption of improved practices as indirect benefits in normal years.[3] More specifically, we have four sets of findings. First, the new technology induces the modernization of farmers' production practices. During both years, treatment farmers are less likely to use the traditional planting method of manually broadcasting seedlings. Instead, they are more likely to use the more labor-intensive manual transplantation method. Specifically, plots cultivated by treatment farmers are 22 percent less likely to be planted using broadcasting in year one. This effect rises to approximately 33 percent during the second year of the experiment. In addition, plots cultivated by treatment farmers are around 14 percent less likely to be cultivated with traditional seed varieties that are generally more flood tolerant but lower yielding on average

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[2]Elongation is the natural response of the rice plant to flooding. However, the plant loses its stored energy while elongating and fails to regrow after floodwaters recede. Swarna-Sub1 represses this elongation response and allows the plant to more effectively grow after flooding ends (Xu et al. 2006; Fukao and Bailey-Serres 2008). Excluding flood tolerance, Swarna-Sub1 is otherwise genetically identical to Swarna—a fact that has been extensively documented by agricultural scientists (Neeraja et al. 2007; Bailey-Serres et al. 2010; Mackill et al. 2012). Therefore, the technology reduces downside risk by reducing the loss in yield during flooding while leaving it unaffected during normal years. This has been shown in agronomic trials (Singh, Mackill, and Ismail 2009). We verify the agronomic property of the technology in farmers' fields using variation in the length of flooding during year one of our study (Dar et al. 2013).

[3]We focus our analysis on rice in the wet season because it is the main crop for a vast majority of the sample. Due to a lack of irrigation only 20 percent of farmers in the sample grow a dry season crop.

than the Swarna variety. Finally, we show some evidence that availability of these new seeds causes more area to be cultivated, partly due to decreased fallowing of low-lying and low-quality lands during year two.

Second, we show that improved technology crowds in more fertilizer use. Conditional on total area cultivated, farmers given access to better technology spend around 10 percent more on fertilizer during the second year of cultivation. This effect is entirely concentrated on the types of fertilizer that are used earlier in the growing season closer to planting time when the risk of crop loss due to flooding is high.

Our third set of findings is on credit usage and savings behavior. Treatment farmers are 36 percent more likely to utilize credit during year two. These loans are primarily agricultural loans distributed by local cooperatives early in the growing season. This effect can plausibly be explained by either demand or supply-side responses in the credit market. That is, the technology decreases the probability of the low production state, which could increase the demand for credit. Alternatively, reducing downside risk could increase the supply of credit by decreasing default risk. Our design does not allow us to distinguish between these alternative mechanisms.[4]

Farmers given access to improved technology also reduce the share of the harvest that is stored for future consumption by five percentage points. A plausible interpretation of this finding is that reducing downside risk with innovation decreases the need to store rice in order to protect against future production variability. Two facts are consistent with this explanation. First, a simple calculation shows that after harvest households set aside more rice than is needed to feed their family for the entire year. Second, the effect of the technology on the storage rate is smaller for households that are at least partially insured by access to government subsidized rice. However, we cannot fully rule out alternative explanations and thus we interpret these results with caution.

Fourth, we quantify the effects of crowd-in on productivity by exploiting the fact that the second year of our experiment was a nonflood year. Given that the new and old technologies are identical when there is no flooding, there should be no productivity effects in the absence of any increased investment by farmers. Instead, we show that access to the technology caused rice yield to increase by approximately 280 kilograms per hectare, or around 10 percent. We consider this to be the overall crowd-in effect of the new technology on agricultural productivity.[5]

How large are these indirect benefits of the new technology when compared to the expected agronomic benefits of the technology over time? We use two pieces of information to calculate expected agronomic benefits: the measured yield benefits obtained on experimental plots conditional on flooding and the average probability of flooding for fields in our sample. Starting with the probability of flooding, we use GIS coordinates of plots in our sample along with 11 years of satellite imagery to approximate the probability that a plot in the sample will be flooded in a given

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[4] The supply-side explanation seems more likely given that loan liabilities are often waived by cooperatives after years of heavy flooding or drought.

[5] Separating the effect of a new technology into purely technical (agronomic) and crowd-in effects is indeed challenging from an empirical standpoint (Beaman et al. 2013). Focusing on new seed varieties in agriculture, the only attempt at separating the agronomic benefits from gains due to crowd-in rely on time series decompositions where complementary inputs are measured as a total factor productivity (TFP) residual in productivity regressions (Evenson and Gollin 2003).

year. We find this probability to be approximately 0.19. We combine this with evidence from controlled laboratory experiments showing the maximum yield gain of Swarna-Sub1 under flooding to be approximately 2 tons per hectare (Singh, Mackill, and Ismail 2009).[6] Combining the two estimates, the expected yield gain due to the purely technical features of the technology is at most 380 kilograms per hectare. This is striking given that crowd-in induces yield gains of around 280 kilograms per hectare. Put differently, crowd-in accounts for at least 43 percent of the overall yield gains of the new technology.

What is the mechanism that explains why these new technologies generate gains through inducing adoption of other inputs and practices? We argue that there are three likely channels. First, by reducing losses during flooding, the technology could have a direct effect on the marginal product of inputs. This would naturally generate factor deepening. Second, there is a downside risk effect which results from the fact that the technology increases *overall* output and income in low-productivity states when the marginal product of input use is low. Reducing downside risk in this way has the effect of both increasing the expected income (the first moment) and reducing the variance of income (the true risk factor). Third, by increasing *expected* income, the technology could generate a wealth effect if farmers' decisions are based on the expected level of output.

While our experiment is not designed to distinguish between these explanations, we give suggestive evidence that the risk effect is an important channel. We show that effects on decision making exist—but are smaller—on plots that are not cultivated with the new technology. This result suggests that shifting input demands due to effects on marginal productivity cannot be the only explanation of the results. However, this is only suggestive evidence because there is undoubtedly selection on the types of plots where the new technology is cultivated. We attempt to reduce such selection concerns by including controls for plot characteristics as well as by selectively dropping the lowest-productivity plots of control farmers during this analysis.

We also provide some supporting evidence that the expected income channel cannot explain the observed factor deepening. We exploit variation in flood intensity during the first year of the study to calculate the duration of the flood shock that would generate a change in output that is roughly equivalent to the expected output gain of the new technology. This equivalent flood shock should generate effects that are of a similar magnitude to our estimated effects if our results are explained by the expected income channel. We do not find evidence for this in the data.

Technologies such as this that make staple crops more tolerant to droughts and floods are a major recent innovation in agriculture. While the Green Revolution benefited much of the world, it is well recognized that rainfed areas that are prone to weather extremes benefited much less. The development of technologies that are more tolerant to weather extremes is considered to be one of the key components of

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[6]This estimate is in the range of estimates from other controlled on-farm trials discussed in Mackill et al. (2012). However, this is a very conservative upper-bound estimate for the *absolute* gains in farmers' fields because baseline yields of farmers in our sample under normal conditions are approximately only 60 percent of those observed in controlled on-farm trials. In addition, controlled trials show that the two technologies produce similar yields when submergence does not occur (Singh, Mackill, and Ismail 2009).

the world's next Green Revolution (Pingali 2012).[7] Our results suggest that a significant share of the gains from this type of technological progress will come from crowd-in effects where farmers are induced to adopt better agricultural practices and other modern inputs.

This paper is the first to consider how improved technology can help close the gap between recommended and actual cultivation practices and input use by smallholder farmers. In particular, farmers fail to adopt improved practices and use few inputs because too often existing seed varieties are not well suited to their local conditions. Technological innovations that improve seed varieties and make them better adapted to local conditions help solve part of the puzzle of inferior cultivation practices and low input use in developing country agriculture.

In addition, our paper presents a new solution to the problem of uninsured risk in developing country agriculture. Donovan (2014) uses a general equilibrium model to show that uninsured risk explains low intermediate input use in developing countries. As a result, uninsured risk contributes significantly to cross-country differences in agricultural productivity. The leading proposed solution is the reduction of exposure to risk through weather insurance, particularly index-based insurance. Empirical results indeed support the proposition that reducing agricultural risk with weather insurance can lead to significant increases in agricultural investment (Mobarak and Rosenzweig 2013; Cole, Giné, and Vickery 2013; Karlan et al. 2014; Elabed and Carter 2014).

While these studies clearly establish the importance of uninsured risk for agricultural investment, we show the promise of technological progress as a meaningful solution to the problem. This is important because the adoption of weather insurance has often remained low in the absence of high subsidies (Mobarak and Rosenzweig 2013; Cole et al. 2013; Dercon et al. 2014; Karlan et al. 2014).[8] This begs the question of whether there are other instruments that can protect against risk and induce greater investment in agriculture. Our results indicate that improved agricultural technology can be one such instrument.

Finally, our results make a contribution to the literature on possible adaptations to climate change. Model predictions suggest that the risk of weather extremes—including severe flooding—will become higher as a consequence of climate shocks (Milly et al. 2002; Hirabayashi et al. 2013). Our results indicate that new technologies which increase resilience to these events not only represent a potential protection from climate shocks, they also create benefits by causing productivity gains during normal years.

The rest of this paper is organized as follows. Section I discusses the various channels through which a risk-reducing seed variety can affect input use. In Section II we outline the experimental design and the data collection. Section III presents results,

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[7] Indeed, scientists have recently invested heavily in developing new seed varieties that are tolerant to various weather stresses. These investments include flood tolerance in rice (Xu et al. 2006; Hattori et al. 2009), drought tolerance in rice and maize (Capell, Bassie, and Christou 2004; Karaba et al. 2007; Nelson et al. 2007), and cold tolerance in rice (Fujino et al. 2008).

[8] The leading explanations pointed to by the literature are high basis risk with index-based insurance, lack of trust in the provider, high loading cost, credit constraints, and insufficient understanding of the concept of insurance (Giné, Townsend, and Vickery 2008; Cole et al. 2013; Cai, de Janvry, and Sadoulet 2015).

while Section IV focuses on mechanisms that could potentially explain these results. Section V concludes.

I. Technological Change and Input Use

In this section we discuss in more detail the mechanisms that could explain our findings. Here we focus on the intuition and present the details of our theoretical model in online Appendix A. We build on this discussion in Section IV when providing empirical analysis on potential mechanisms.

There are three mechanisms through which introducing this new technology can change input use: an expected income effect, a marginal productivity effect, and a risk effect. Focusing on the expected income effect, the technology has a positive effect on expected output because it increases output in the flood state but leaves output unchanged in a nonflood year. This could increase input use in two ways. First, forward-looking farmers could base input-use decisions off future wealth. Second, increasing expected wealth changes the level of absolute risk aversion when preferences are not constant absolute risk aversion. Most importantly, a factor deepening effect would result if preferences exhibit decreasing absolute risk aversion.

The second mechanism is simple technical complementarity between the new seed variety and an input. This "marginal productivity effect" would explain additional input use because adoption of the technology simply coincides with the input becoming more productive. Importantly, this effect could arise independently of risk. That is, technical complementarity would induce even risk-neutral farmers to increase input use in response to the technology. In principle, there is no reason to believe that the flood tolerance trait has any effect on the marginal product of inputs during the nonflood state.

Third, the technology reduces the riskiness of input use. This downside risk effect is large when the new seed increases production in states of nature where the marginal value of the input is low and thus there are large losses from investing in inputs. The intuition for this is that spending on inputs during a flood year turns out to be less painful to the farmer because the technology increases production, thus partially stabilizing consumption. Importantly, one can show that this risk effect is strictly increasing with the coefficient of absolute risk aversion.

II. Experimental Design and Data

In this section we present the details of the experimental design and sampling. In addition, we outline the timing of data collection and present summary statistics on both village and household characteristics.

A. *Experimental Design*

Our sample is drawn from villages in flood-prone areas of the Bhadrak and Balasore districts of northern Odisha. This area is suitable for the study because flood risk is high, Swarna is widely grown, and Swarna-Sub1 was still unavailable to farmers in May 2011 when the project was initiated. The villages were identified from two sources. In Bhadrak, satellite imagery was matched to a GIS database of

villages to identify villages that were affected by flooding.[9] A random subset of 64 affected villages was selected for inclusion in the study. In Balasore, we used a list of flood-prone villages established by our local non-governmental organization (NGO) partner to randomly select 64 villages.[10] Figure 1 displays a map of the study area and the villages included. As is seen on the map, almost all of the study villages are in low-lying coastal areas.

We first randomly divided the 128 sample villages into treatment and control groups. This village-level randomization was stratified by blocks, which are administrative units that consist of 100–200 villages. The 128 sample villages are spread across 8 blocks. A local government official was then visited in all villages to generate a list of 25 farmers using Swarna and affected by flooding. Using this list, 5 farmers were randomly selected in each of the 64 treatment villages to receive minikits containing 5 kilograms of Swarna-Sub1 seeds.[11] The seeds were delivered in June 2011, which is right before planting. Our comparison group consists of 10 randomly selected nonrecipients in treatment villages and 5 randomly selected farmers in the 64 control villages.[12]

In addition to the minikit, treatment farmers were provided with a two-page information sheet on Swarna-Sub1. The information sheet had two important components. First, we included pictures from farmer-managed trials showing the clear productivity gains of Swarna-Sub1 after flooding. Second, the information sheet conveyed that other than flood tolerance, Swarna-Sub1 is identical to Swarna. Importantly, the sheet did not suggest any management practices such as how to plant the field or how much fertilizer to use. Instead, farmers were informed that Swarna-Sub1 can be managed exactly like Swarna.

Importantly, several villages in the sample were affected by heavy flooding during September 2011. Approximately 40 percent of plots in our sample were fully submerged—and detectable with satellite images—during the flood. While inundation occurred in both districts of the sample, the heaviest flooding occurred in the southernmost district of Bhadrak.

The implementing NGO did not provide additional seeds to treatment farmers after year one. Given that Swarna-Sub1 seeds were not available on the market, the only way to continue using the variety was to save a portion of the year one harvest as seeds for cultivation during year two.

B. Data Collection

Our first follow-up survey was conducted in March 2012 after the first year's crop was harvested. A total of 1,248 farmers were reached, achieving a response rate of 97.7 percent.[13] Compliance with the treatment during the first year was near

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[9] We used RADARSAT images (100 m resolution) from 2008 to identify villages affected by flooding.

[10] The satellite imagery of historic floods was not available at the time of village selection.

[11] Five kilograms of seed is sufficient to cultivate 0.1 to 0.2 hectares, or approximately 10 to 20 percent of average cultivated area. This is the standard minikit size for cereal crops in India.

[12] We show in Table A9 that our main outcomes are not significantly different between nonrecipients in treatment and control farmers. Thus, the technology did not generate significant within-village spillover effects. Therefore, we retain both sets of nonrecipient farmers in all specifications.

[13] This small level of attrition is balanced across treatment and control. Enumerators were not able to contact farmers in one control village due to disagreement with local village leaders about participation in the study. The
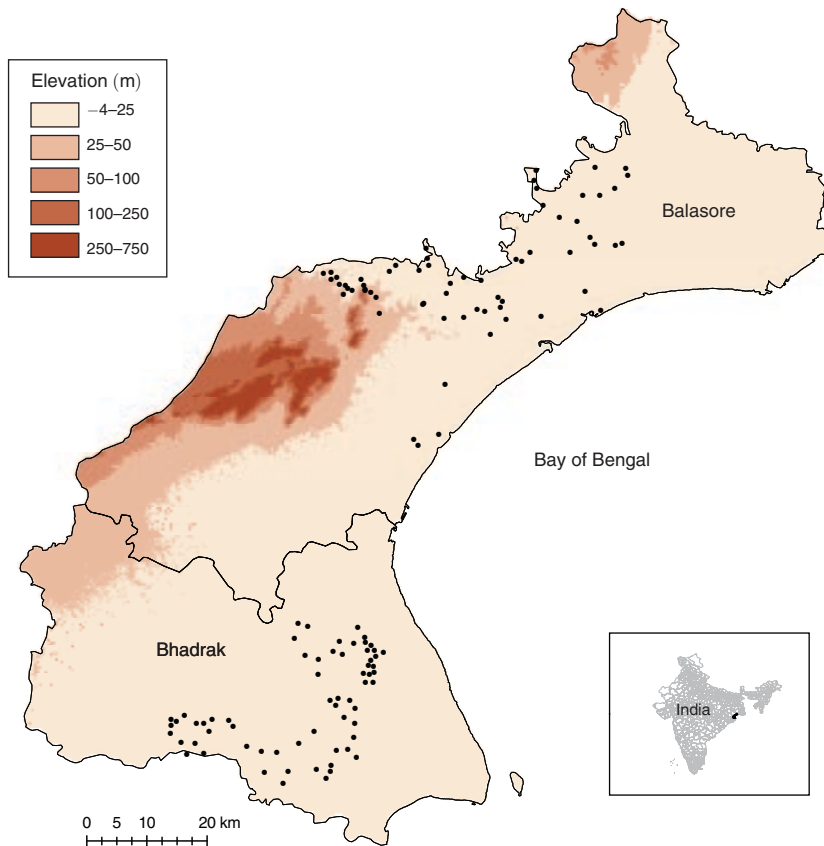
FIGURE 1. LOCATION OF VILLAGES IN ODISHA

universal. Only 2 out of the 320 treatment farmers declined to receive the minikit and cultivate it on their land. Treatment farmers cultivated approximately 14 percent of their land with Swarna-Sub1.

The second follow-up survey was carried out one year later after the growing season for year two. A total of 1,237 of the farmers surveyed during 2012 were reached again during this survey. Important outcomes of interest are area cultivated, farm-level information on inputs, allocation of output across uses, and credit utilization. In addition, a plot-level module on seed variety choice, planting methods, and production was administered.

Compliance with the treatment during the second year—defined as continued cultivation of Swarna-Sub1—was high. Seventy-six percent of minikit recipients cultivated the technology during year two.[14] The average number of plots sown with Swarna-Sub1 among minikit recipients was 1.5. Average land area cultivated

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results reported are for the remaining 127 villages.

[14] The most common reason for disadoption was crop loss during year one. Swarna-Sub1 is not suitable for low areas where water remains stagnant for more than two weeks after flooding (Singh, Mackill, and Ismail 2011). Swarna-Sub1 that was planted in these areas during year one was lost.

TABLE 1—CHARACTERISTICS OF SAMPLE VILLAGES AND OTHER LOW-LYING VILLAGES IN
ODISHA, WEST BENGAL, AND BIHAR

	In experiment	Other villages in 3 states
Number households	177.72	307.66
	(175.536)	(408.872)
Household size	5.31	5.26
	(0.891)	(0.843)
Share scheduled caste	0.20	0.23
	(0.202)	(0.246)
Share scheduled tribe	0.09	0.07
	(0.181)	(0.183)
Share cultivating land	0.12	0.09
	(0.069)	(0.067)
Share agricultural laborers	0.06	0.09
	(0.066)	(0.082)
Literacy rate	0.60	0.51
	(0.110)	(0.182)

Notes: All data are taken from the 2001 population census. Column 1 pertains to 125 villages in Odisha that were part of the experiment. Three of the 128 sample villages were not successfully matched to the 2001 census. Column 2 pertains to the other 55,324 villages in Odisha, Bihar, and West Bengal that have an elevation of less than 56 meters (the maximum elevation of the sample villages). Numbers in parentheses are standard deviations.

with Swarna-Sub1 was 0.33 hectares, or approximately one-third of average land-holdings. Conversely, only 10.1 percent of control farmers cultivated Swarna-Sub1 during year two. We show in Table A1 that this was a direct result of seed transfers from original recipients: 13.3 percent of control farmers cultivated Swarna-Sub1 in treatment villages and only 3.3 percent did so in control villages. Given the low levels of noncompliance across the two years of the study, we take a conservative approach and report intention-to-treat (ITT) results throughout the paper.

C. *Summary Statistics*

Villages in the sample are fairly representative of the low-lying villages in the flood-prone states of Bihar, Odisha, and West Bengal. Table 1 shows village characteristics from the 2001 census.[15] With the exception of village size, the sample villages are roughly similar to all villages in low-lying areas of the three states.

Turning to the household-level data from our sample, Panel A of Table 2 reports summary statistics of variables that are likely predetermined, but were collected during the first follow-up survey. Most importantly, treatment and control households look similar on most predetermined characteristics. Farms in the sample are small. Average landholdings are less than one hectare. While electricity is fairly widespread, few households have access to piped water. Most households rely on either village or private tubewells for water. Approximately 56 percent of households have below the poverty line (BPL) cards, which give them access to government supports such as a monthly allotment of subsidized rice. Panel B of the table

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[15] Villages in the other three states were included if the elevation was below 56 meters, the maximum elevation in our sample of villages.

Table 2—Mean Values of Household Characteristics and Flood Exposure of Plots by Treatment Status

	Control	Treatment	*p*-value of difference
Panel A. Household characteristics			
Land owned in hectares	0.810	0.868	0.22
HH has private tubewell	0.332	0.325	0.82
HH has piped water	0.035	0.057	0.09
HH has refrigerator	0.078	0.076	0.92
HH has television	0.628	0.605	0.46
Education of farmer	6.896	6.946	0.83
Age of farmer	51.191	51.783	0.44
HH has thatched roof	0.557	0.548	0.78
HH has latrine	0.289	0.354	0.03
HH has electricity	0.843	0.822	0.38
HH has below poverty line card	0.574	0.559	0.64
ST or SC	0.189	0.176	0.61
Panel B. Flood exposure of cultivated plots			
Share plots low land	0.335	0.357	0.37
Share plots medium land	0.569	0.571	0.94
Share plots high land	0.081	0.067	0.34
Average flood duration in year 1	5.518	5.887	0.23
Joint *p*-value of household characteristics	0.26		

Notes: Data are from year 1 follow-up. Values in columns 1 and 2 are means. *p*-values in column 3 are based on *t*-tests of equality of means. ST refers to scheduled tribe and SC refers to scheduled caste. The *p*-value from the joint regression is the *p*-value from the joint test of all covariates when treatment assignment is regressed on all covariates.

shows some characteristics of the plots held by farmers in our sample. Farmers cultivate an average of around 3.5 plots and one-third of those are in lower-lying areas. On average, farmers report that a plot was flooded for around 5.5 to 6 days during the first year.

III. Results

This section presents results supporting the argument that improved technology modernizes agriculture by increasing the use of modern agricultural practices and inputs. We first outline the estimation approach and then present the main results on cultivation practices, fertilizer use, rice storage, and credit. We then show that the technology leads to substantial gains in land productivity—even in year two when there was no flooding. We then benchmark the year two productivity gains due to crowd-in against the expected technical gains that arise from flood tolerance. Finally, we also consider whether the additional investments that were induced translate into profitability gains rather than just productivity gains.

A. *Estimation Approach*

Our main approach is to use the random distribution of Swarna-Sub1 seeds to explain management choices at both the farm and plot level. The baseline specification is therefore

$$(1) \qquad y_{ivb} = \beta_0 + \beta_1 treatment_{ivb} + \alpha_b + \varepsilon_{ivb},$$

where y_{ivb} is an outcome observed for farmer i in village v and block b, and α_b is a fixed effect for the block, which was a stratification variable for the village-level randomization. The error term is clustered at the village level since this corresponds to the first tier of randomization. We continue to use the farmer-level treatment indicator when outcomes are observed at the plot level. The estimate of β_1 in the plot-level regressions therefore represents an average effect across all plots, not just the plots cultivated with Swarna-Sub1.

This intention to treat (ITT) estimate of β_1 would obviously be attenuated if there were either significant disadoption by minikit recipients or adoption by nonrecipients. As we noted above, compliance was nearly 100 percent in the first year of the study. Given the small amount of noncompliance during year two, instrumental variables estimates of treatment on the treated (TOT) effects would be larger by a factor of approximately 1.5. We report the ITT estimates as they carry the most policy relevance when dissemination of the new technology naturally leads to some disadoption due to imperfect targeting.

We only use the variation generated by the experiment by including only the treatment indicator and the strata (block) fixed effects in our main specifications. However, we show in Tables A2 to A6 that our main results are unaffected by controlling for household covariates. Finally, when our data allow, we estimate our main specifications separately for years one and two.

B. *Cultivation Practices and Inputs*

The improved technology led to a small expansion in cultivated area. Column 1 of Table 3 shows that access to Swarna-Sub1 led to an immediate increase in area planted of 0.07 hectares or around a 9 percent increase. Panel B shows that this effect rose only slightly during year two. Overall, the result suggests that some land is left uncultivated due to flooding risk and that improved technologies that address this brings this land into production. Also, we show in Table A7 that treatment farmers were significantly less likely to take land out of production (fallowing) during the second year, in particular plots that are low-lying and considered to be lower quality. The decreased likelihood of taking these flood-prone lands out of production partly explains the observed effects on cultivated area during year two. Table A8 shows that the area effect is driven by cultivation of additional plots, not increased area of existing plots.

While Swarna is the most popular rice variety grown in the sample region, farmers often use local "traditional" varieties that are not considered modern and high yielding. These varieties have a high capacity to survive during flooding due to their ability to rapidly elongate when submerged (Voesenek and Bailey-Serres 2009).[16] We show two pieces of evidence in the online Appendix that flooding risk is one

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[16] We have yet to distinguish between flash flooding, where Swarna-Sub1 performs well, and stagnant water accumulation. Flash flood areas are those where flooding occurs and water recedes after a period of one day to around two weeks. Stagnant water areas are those where water remains partially submerging the crop even after floodwaters recede. Our findings in Dar et al. (2013) and other research (i.e., Singh, Mackill, and Ismail 2011) show that Swarna-Sub1 does not tolerate stress due to stagnant water of more than approximately 15 days.

TABLE 3—EFFECTS ON CULTIVATION PRACTICES

	Area planted (1)	log area (2)	Use Swarna (3)	Use TV (4)	Broadcast (5)
Panel A. Year 1					
Original minikit recipient	0.068 (0.045)	0.088 (0.048)	−0.157 (0.018)	−0.029 (0.016)	−0.022 (0.012)
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.92	−0.36	0.47	0.21	0.10
Observations	1,248	1,238	4,215	4,214	4,221
R^2	0.167	0.197	0.129	0.153	0.094
Panel B. Year 2					
Original minikit recipient	0.109 (0.056)	0.098 (0.044)	−0.101 (0.017)	−0.041 (0.016)	−0.063 (0.017)
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	1.00	−0.20	0.36	0.28	0.19
Observations	1,237	1,175	4,589	4,588	4,582
R^2	0.112	0.161	0.115	0.270	0.242

Notes: Dependent variable is total rice area planted in hectares (column 1), log of total rice area (column 2), an indicator for using Swarna on the plot (column 3), an indicator for using a traditional seed variety on the plot (column 4), and an indicator for planting the plot using the broadcasting technique (column 5). The observations are at the farmer level in columns 1 and 2 and at the plot level in columns 3 through 5. Standard errors that are clustered at the village level are reported in parentheses.

of the reasons this traditional technology is still used. First, when asked, farmers directly state that one of the main reasons for adopting these varieties is their tolerance to flooding (see Figure A1). Second, in Figure A2 we show that these varieties had higher survival rates in heavily flooded areas during year one.

Not surprisingly, column 3 of Table 3 shows that plots cultivated by treatment farmers were less likely to be sown with Swarna by 15.7 percentage points and 10.1 percentage points in years one and two, respectively. More interestingly, there was an immediate reduction in the use of traditional varieties by 2.9 percentage points (14 percent) during year one and 4.1 percentage points (or 14.6 percent) during year two (column 4). Thus, the crowding out of traditional varieties is one of the channels through which the innovation affects output.

In addition to modernization of seed varieties, the technology also led to a modernization of planting methods. Column 5 shows that farmers given access to the improved technology were less likely to opt for the cheaper, less productive, and traditional planting method of manually broadcasting seeds. Instead, treatment farmers were more likely to use the more labor-intensive method of manually transplanting seedlings.[17] Panel A shows that plots cultivated by treatment farmers were 2.2 percentage points (around 22 percent) less likely to be sown using the broadcasting method during year 1. During year 2, this effect rose to 6.3 percentage points, or around 33 percent.

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[17] Transplanting involves raising seedlings on a small portion of land, pulling and bundling the seedlings after approximately three weeks, and planting the seedlings manually in the main field. While broadcasting is a popular planting technique in flood-prone areas due to a lower labor requirement, increased competition from weeds reduces yields (Khush 1997; Rao et al. 2007).

TABLE 4—EFFECTS ON FERTILIZER USAGE DURING YEAR TWO, CONDITIONAL ON CULTIVATED AREA

	All (1)	Urea (2)	DAP (3)	MOP (4)	Gromor (5)
Original minikit recipient	396.703 (179.631)	13.428 (34.372)	393.768 (136.410)	90.579 (58.170)	−101.073 (67.759)
Rice area (hectares)	3,835.891 (315.559)	694.814 (108.483)	2,288.634 (253.521)	623.535 (132.287)	228.909 (66.481)
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	3,781.48	664.70	2,016.80	702.82	397.15
Observations	1,237	1,237	1,237	1,237	1,237
R^2	0.619	0.496	0.526	0.279	0.064

Notes: Dependent variable is fertilizer expenditure in rupees. The column labels indicate the type of fertilizer. All observations are from year two of the experiment and are at the farmer level. Standard errors that are clustered at the village level are reported in parentheses.

Improved technology also induced greater fertilizer use during year two.[18] Column 1 of Table 4 shows that conditional on cultivated area, total fertilizer expenditures rose by 397 Rs or 10.5 percent for treatment farmers. Columns 2 through 5 show that this increase in fertilizer expenditure is almost entirely concentrated on phosphate (DAP) and potassium (MOP) fertilizers. We show in Figure A3 that phosphate and potassium fertilizers are generally used earlier in the growing season.[19] Combining these two facts, the improved technology resulted in increased fertilizer use only for fertilizers that are used earlier in the growing season when the risk of exposure to flooding is highest. This provides further evidence that this technology led to additional investment near planting time and helped close the gap between actual and recommended fertilizer application.[20]

C. *Storage and Credit*

Farmers in the sample store large amounts of rice after each harvest relative to their annual consumption. The average total rice harvest amongst cultivators in our sample was 2,945 kg. An average of 1,711 kg of the harvest was consumed or set aside for future consumption.[21] This amount is enough to feed roughly 11 adults for

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[18] Our first follow-up survey only included fertilizer use on the Swarna-Sub1 plot of treatment farmers and the largest Swarna plot of control farmers. Due to plot selection issues, we do not use these data to estimate effects on fertilizer usage.

[19] This is also consistent with basic agronomic recommendations based on the functions of the different nutrients. In particular, phosphorous (DAP) and potassium (MOP) contribute mostly to soil conditioning and root development, and are applied early in the growing season. In contrast, nitrogen—in the form of urea—contributes to healthy plant and leaf development and therefore is mostly applied later in the season after the plant is more fully developed and leaf growth is occurring.

[20] Fertilizer application in our sample is still below recommendations in spite of high subsidies. An approximate recommendation for our sample area is a per-hectare application of 80 kilograms of nitrogen (N), 40 kilograms of phosphorous (P), and 40 kilograms of potassium (K). The median farmer in the control group during year two applied 57.8 kg of nitrogen, 34 kg of phosphorous, and 15.5 kg of potassium for each hectare of land cultivated. In contrast, the median farmer in the treatment group applied 59.7 kg of nitrogen, 39.1 kg of phosphorous, and 18.3 kg of potassium.

[21] Since our survey was conducted shortly after the harvest and postharvest production practices, most of the amount indicated for consumption had yet to be consumed at the time of the survey.

a year.[22] Average household size in the villages in our sample is 5.3 persons. While we acknowledge that stored rice is a liquid asset that can be sold upon family need, one plausible explanation for this large amount of rice storage is the need to insure against future consumption variability.

Farmers receiving Swarna-Sub1 store a smaller share of their harvest for future consumption. Column 1 in Table 5 shows that after year one, treatment farmers stored 2.6 percentage points less output for consumption. While this effect is not quite statistically significant, panel B shows that the effect after year two rises to 5 percentage points and is statistically significant.[23] The magnitude of the effect is not trivial. It amounts to approximately 150 kilograms, or enough to meet the consumption needs of 1 household member for the entire year. Column 2 of panel B shows that the storage effect during year two is concentrated among households who *do not* hold below the poverty line (BPL) cards. BPL cards serve as consumption insurance because they entitle households to purchase 30 kilograms of rice per month—an amount that is enough to feed approximately two adults—at highly subsidized rates.[24] This additional heterogeneity is consistent with the technology decreasing the need to use storage as a form of consumption insurance.

In addition to reducing storage rates, improved technology that reduces downside risk increases the uptake of agricultural credit. Columns 3–5 of Table 5 focus on binary indicators of household access to credit. Column 3 shows that credit uptake increased by 6.3 percentage points immediately during year 1, but the effect is not statistically significant at conventional levels. Given average credit uptake of 43 percent, this effect amounts to about a 15 percent increase. Average uptake of new loans across the entire sample was much smaller (19 percent) during year two. However, column 3 in Panel B shows that treatment farmers were 6.8 percentage points more likely to take out a new loan during the time between planting and harvesting for year two. This amounts to a meaningful 36 percent increase in credit uptake. Columns 4 and 5 show that a large portion of the effect is driven by loans originating from agricultural cooperatives.

In contrast to inputs, the results on rice storage and credit uptake are unlikely to be explained by shifts in the marginal productivity of inputs. Rather, storage offers insurance against low or zero production during flooding. By increasing the overall level of production during flooding, the technology substitutes directly for storage. Utilization of agricultural credit increases either due to a demand effect where the increase in expected production in the future makes borrowing more desirable, or a supply effect where credit constraints are a function of the borrower's expected production.[25]

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[22] This calculation is based on an average annual consumption in rural Odisha of 158 kilograms per capita per year, as reported in the sixty-fourth round of the National Sample Survey.

[23] A similar regression where the dependent variable is the share of rice sold delivers a coefficient estimate of 0.047. Thus, much of the output that was not stored for consumption was instead sold.

[24] The price of BPL rice is 1 to 2 Rs per kilogram while the market price of similar rice is 20 Rs or higher.

[25] Also, increased uptake of credit could play a role in decreasing savings of stored rice: additional credit could further crowd in input use at planting, which increases output and decreases the need for precautionary savings (Fulford 2013).

TABLE 5—EFFECTS ON RICE STORAGE AND CREDIT UPTAKE

	Storage rate (1)	Storage rate (2)	Loan (3)	Coop loan (4)	Other loan (5)
Panel A. Year 1					
Original minikit recipient	−0.026 (0.015)	−0.016 (0.027)	0.063 (0.039)	0.033 (0.028)	0.030 (0.032)
Original minikit recipient*HH has BPL card		−0.017 (0.034)			
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.73	0.73	0.43	0.24	0.19
Observations	1,183	1,180	1,248	1,248	1,248
R^2	0.113	0.117	0.122	0.154	0.055
Panel B. Year 2					
Original minikit recipient	−0.050 (0.017)	−0.085 (0.024)	0.068 (0.027)	0.050 (0.024)	0.023 (0.019)
Original minikit recipient*HH has BPL card		0.061 (0.031)			
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.70	0.70	0.19	0.12	0.08
Observations	1,167	1,164	1,237	1,230	1,237
R^2	0.070	0.073	0.058	0.057	0.014

Notes: Dependent variable is the share of the total rice harvest that was stored for future consumption (columns 1 and 2), an indicator for having a loan (column 3), an indicator for having a loan from an agricultural cooperative (column 4), and an indicator for having a loan from another source (column 5). Other sources are banks, input sellers, self-help groups, microfinance institutions (MFI), friends/relatives, or money lenders. Standard errors that are clustered at the village level are reported in parentheses.

D. *Effects on Productivity*

The results indicate that improved technology induces the adoption of several other modern inputs and management practices. A natural next question is to ask how these changes translate into productivity gains.

There is a noticeable increase in yield for plots cultivated by farmers with access to Swarna-Sub1. Figure 2 displays the estimated kernel densities of yield by treatment status for both years of the study. Focusing on year one, the severe flooding in part of the sample is apparent as there is a significant mass of the distribution at low yields. However, there is also a clear rightward shift in the distribution of yield for treatment farmers. This effect is a combination of the purely technical gains in flooded areas with the gains due to the small crowd-in effects reported above.

Panel B shows that there is a clear rightward shift in the distribution for treatment farmers during year two when flooding did not occur. This effect occurs throughout the distribution of yield, suggesting that it is not concentrated on the lowest or highest productivity farmers.

The regression results in Table 6 are consistent with the graphical evidence. Column 1 shows that the technology led to an increase in yield during year one of 315 kilograms per hectare, or around 14 percent. In year two, when flooding did not occur and all productivity gains are due to crowd-in, treatment farmers harvested an average of 283 kilograms more per hectare cultivated. This translates into a 10 percent increase in productivity.
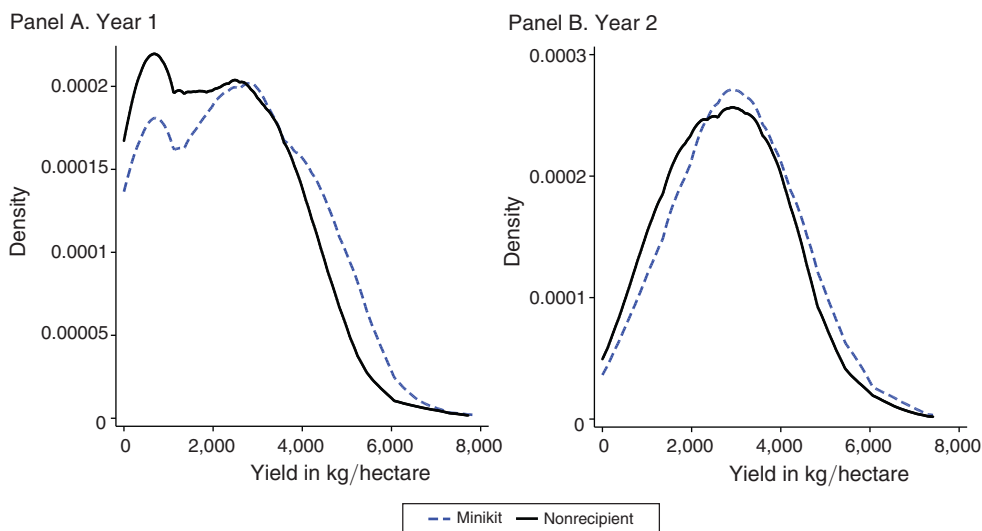
Panel A. Year 1

Panel B. Year 2

FIGURE 2. KERNEL DENSITIES OF PLOT-LEVEL YIELD BY TREATMENT STATUS

Notes: Figure displays estimated kernel densities of yield (kg/hectare) for both years of the study. Densities are estimated across all cultivated plots. The dashed lines are densities for all plots cultivated by minikit recipients, regardless of seed variety choice on those plots. The solid lines are densities for all plots cultivated by control farmers.

TABLE 6—EFFECTS ON PRODUCTIVITY

	Year 1	Year 2			
	(1)	(2)	(3)	(4)	(5)
Original minikit recipient	314.97	283.45	230.30	196.54	169.14
	(86.28)	(77.48)	(73.73)	(68.06)	(64.84)
Broadcast planting			−801.22	−679.36	−419.08
			(129.45)	(117.53)	(108.50)
Tons fertilizer per hectare				4,350.39	3,237.30
				(997.70)	(831.35)
Tons fertilizer per hectare^2				−4,025.26	−2,942.84
				(1,628.52)	(1,266.48)
Traditional variety					−442.46
					(70.86)
Irrigated					711.64
					(92.21)
Has credit					150.79
					(69.04)
Block fixed effects	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	2,213.39	2,817.97	2,819.53	2,819.53	2,819.13
Observations	4,184	4,573	4,568	4,568	4,514
R^2	0.409	0.159	0.200	0.236	0.302

Notes: Dependent variable in all regressions is yield in kg/hectare. Estimation data are at the plot level. Broadcast planting, traditional variety, and irrigated are measured at the plot level; fertilizer per hectare and credit are measured at the farmer level. Standard errors that are clustered at the village level are reported in parentheses.

As a method of investigating whether the crowd-in effect is a channel through which improved technology affects productivity, we sequentially add our main outcome measures as regressors to the yield equation. Adding these endogenous outcomes as controls should attenuate the reduced-form productivity effect if the effect is partly operating through these channels.[26] Of course, the coefficients on the endogenous outcome variables represent merely correlations and cannot be interpreted causally.

The conditional productivity effect is substantially lower than the unconditional effect. Columns 3–5 of Table 6 show that accounting for the observed changes in production practices substantially attenuates the productivity effect. In addition, the goodness of fit of the regression approximately doubles. Therefore, the crowd-in effect is an important determinant of the overall productivity effect of the technology.

How large are these indirect effects of the new technology? We next benchmark this crowd-in effect against the expected yield gains from controlled laboratory experiments on agricultural experiment stations. Agronomic benefits reported by experimental stations are importantly measured while input use is held constant and thus the only advantage of the improved technology occurs through its technical superiority. Singh, Mackill, and Ismail (2009) show that the maximum yield benefit of Swarna-Sub1 under 12 days of flooding is approximately 2 tons per hectare. In addition, the absolute magnitude of the yield benefit in farm-trials declines as flood severity worsens beyond 12 days.

To generate the probability that a field in our sample would be flooded during the wet season, we use satellite imagery from past flooding. We used imagery of all flooding in the two districts from 2002 to 2008 and 2011 to 2014 to identify areas affected by flooding.[27] We overlaid these flood areas with the GIS centroid of 1,123 plots cultivated by farmers in our sample. These GIS coordinates were collected for the Swarna-Sub1 plot of treatment farmers and the largest Swarna plot of control farmers. Figure 3 shows the distribution of flooding for these plots across the 11 years for which we had satellite imagery. Notably, the most severe flood year was 2011, the first year of the experiment. Approximately 40 percent of plots were detected as flooded using the satellite images during 2011. Also, there was almost no flooding during the following year: only 2 percent of plots were detected as flood-affected during 2012.

The overall average probability of flooding across the 11 years is 0.19, which is the horizontal line displayed in Figure 3. This average probability is similar across the Swarna and Swarna-Sub1 plots. Combining this with the estimated yield advantage of 2 tons per hectare during flooding, 380 kg per hectare is a very conservative upper-bound estimate of the expected technological gains due to agronomy. Thus, we estimate that the 283 kilogram per hectare gain due to crowd-in effects represents no less than 43 percent of the overall gains from the innovation.

An implication of this finding is that estimated returns of new technologies that do not account for how farmers reoptimize their decisions will significantly understate

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[26] This approach has been used to investigate the channels through which education affects voting (Milligan, Moretti, and Oreopoulos 2004) and the channels through which early-life rainfall shocks affect outcomes later in life (Maccini and Yang 2009). In our case the reduced-form treatment effect that remains after conditioning on inputs can be thought of as a measure of TFP.

[27] These data come from the MODIS satellite and have a resolution of 250 M (http://floodobservatory.colorado.edu/Modis.html. A more detailed description of the data is available on this website).
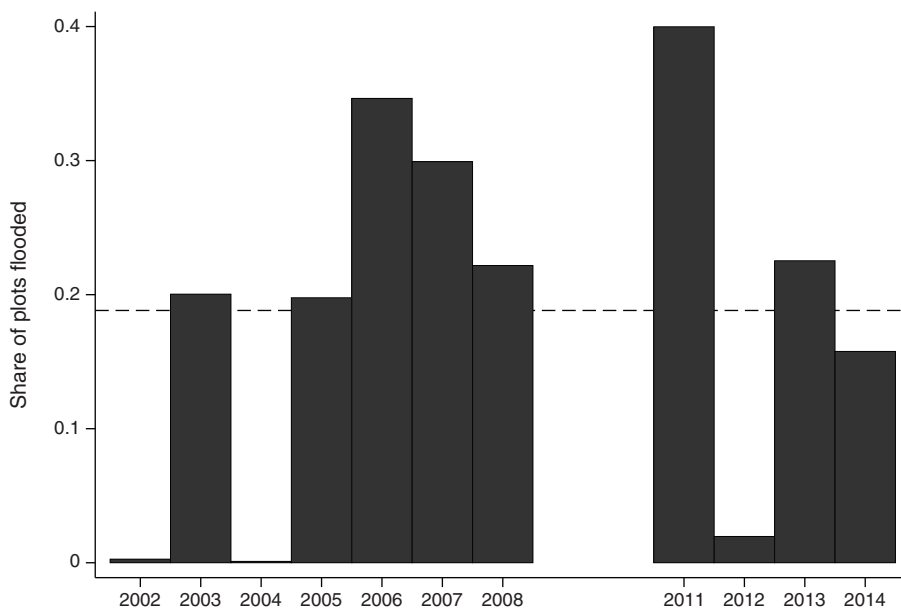
Figure 3. Distribution of Flooding for Sample Plots, 2002–2008 and 2011–2014

Notes: Figure shows the distribution of flooding across time for 1,123 plots that were cultivated by farmers in our sample during year one of the study. The height of each bar is the share of the 1,123 plots that were flooded at least once during the relevant season. Satellite imagery from MODIS for the years 2002–2008 and 2011–2014 were matched with the GIS coordinates of the plot to determine whether a given plot was flooded in each year. The horizontal dashed line represents the overall probability of flooding for plots in the sample, which is 0.19 across the 11 years.

the gains from new technologies. In addition, this result further demonstrates the value of using field experiments to measure the impacts of new agricultural technologies. Studies on experimental plots that don't account for reoptimization of farmers will not deliver the true causal effects of new technologies.

Including these productivity effects, we have shown that the flood-tolerant rice variety has significant impacts on several outcomes of interest. However, we have thus far only considered the outcomes individually and have not adjusted the *p*-values for multiple inference. In Table A10 we show all regression results for the 20 agricultural outcomes measured by our second year follow-up survey. More importantly, we show that adjusting *p*-values for multiple inference by controlling the false discovery rate does not significantly alter the conclusions of our hypothesis tests (Benjamini, Krieger, and Yekutieli 2006; Anderson 2008).

E. *Are Additional Investments Profitable?*

We have shown that increased investment is an important channel through which improved agricultural technologies lead to substantial gains in productivity. In particular, average yield of farmers given access to flood-tolerant rice increases by around 283 kg per hectare (Table 6). This amounts to an increase in revenue per hectare of 2,969 Rs when applying the average output price from our survey of 10.5 Rs per kg. However, the increased investments that drive this increase, such as using

more fertilizer or changing planting techniques, are indeed costly. Therefore, the gains in profitability are undoubtedly lower than the measured productivity gains.

Additional calculations suggest that the incremental costs associated with the observed management changes represent less than half of the gains in revenue. We estimate that the cost increase resulting from the observed changes in management is around 1,103 Rs per hectare. This represents only 37 percent of the estimated revenue gains and therefore suggests that the technology does lead to gains in profitability. We explain the details of this calculation in online Appendix B.

IV. Mechanisms

Our results suggest that an improved technology that decreases the downside risk of production causes farmers to reoptimize along several dimensions. While the results are consistent with reducing risk being one of the important mechanisms, there are some other equally plausible explanations. In this section we consider some alternative tests to investigate whether the data are consistent with these explanations. Importantly, these tests cannot definitively point to risk as the only explanation of our findings. We are therefore cautious to interpret the findings as suggestive that nonrisk mechanisms are not entirely consistent with the data.

A. Shifts in the Marginal Productivity of Inputs

Returning to the discussion above, the marginal productivity effect is one of the channels through which introducing a risk-reducing seed variety could influence input use. If the new variety is a technical complement to an input like fertilizer, then the variety could naturally increase fertilizer use independent of its risk-reducing property. We attempt to rule this out as the only explanation for our results by considering plots that were cultivated by treatment farmers, but were not cultivated with Swarna-Sub1. We estimate our main effects on this subsample of plots. If the results are explained by how the technology itself changes the marginal productivity of these inputs, then there is no reason to expect any effects on these plots.

While the effects are smaller, the effects on productivity, broadcasting, and DAP fertilizer expenditures all persist on plots where Swarna-Sub1 was not used. Column 1 of Table 7 shows a yield effect of 173 kilograms per hectare, or approximately 6 percent. Columns 2 and 3 show that there is no substitution away from other rice varieties on these plots, suggesting that any effects on inputs are not due to which varieties were grown.[28] Column 4 shows that there remains a 4.2 percentage point decrease in the probability of using broadcasting by treatment farmers on the plots not cultivated with the new technology. Finally, plot-level expenditures on DAP fertilizer are higher by around 100 Rs for treatment farmers on non-Swarna-Sub1 plots (column 6). In combination, these results help to rule out the mechanism where the new technology simply increases the marginal products of inputs.

However, an important concern with this approach is the endogeneity of plot choice. If treatment farmers allocated Swarna-Sub1 to their worst lands, then the

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[28] Table A11 shows that the results are robust to controlling for variety fixed effects.

TABLE 7—EFFECTS ESTIMATED FOR SAMPLE OF FIELDS NOT CULTIVATED WITH SWARNA-SUB1

	Yield (1)	Use Swarna (2)	Use TV (3)	Broadcast (4)	Fertilizers All (5)	DAP (6)
Original minikit recipient	172.901 (77.156)	−0.008 (0.021)	0.023 (0.018)	−0.042 (0.019)	63.022 (57.614)	100.389 (47.962)
Area of plot	−223.539 (121.532)	0.006 (0.039)	0.023 (0.037)	0.033 (0.035)	3,538.521 (371.851)	2,094.537 (263.348)
Owned land	34.201 (66.644)	0.062 (0.020)	−0.025 (0.018)	0.055 (0.018)	119.388 (63.060)	87.608 (43.477)
Block fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Land quality indicators	Yes	Yes	Yes	Yes	Yes	Yes
Land slope indicators	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	2,757.37	0.40	0.32	0.20	1,098.14	590.57
Observations	4,087	4,087	4,086	4,082	4,087	4,087
R^2	0.18	0.15	0.31	0.27	0.52	0.43

Notes: Data consist of entire sample of plots not cultivated with Swarna-Sub1 during the second year of the study. The dependent variables are rice yield in kg/hectare (column 1), an indicator for planting the field with Swarna (column 2), an indicator for planting the field with a traditional rice variety (column 3), an indicator for planting using the broadcasting technique (column 4), and total fertilizer expenditures in rupees (columns 5–6). Standard errors that are clustered at the village level are reported in parentheses.

treatment-control comparison on the remaining plots would artificially favor finding effects of treatment on these outcomes.[29] As the first approach to reducing these selection concerns, Table 7 includes controls for self-reported land quality, relative elevation (or slope) of plots, land ownership, and area of the plot. The main effects in the table are therefore all conditional on these potential sources of selection.

We address concern about selection on unobservables by constructing a simple simulation to assess the degree to which these results could be driven by plot-level selection. Treatment farmers cultivate on average 0.235 fewer plots with non-Swarna-Sub1 varieties. This is fairly modest since control farmers cultivate an average of 3.6 plots with these same types of varieties. We construct a simulation where we take each control farmer in the sample and randomly drop one of their plots with a probability of 0.235. We make the simulation exercise as conservative as possible by generating a random number from the unit interval for each control farmer and dropping their lowest-yielding plot if that random number is less than 0.235. This results in a trimmed sample where 184 plots are dropped from the analysis. Importantly, trimming balances the total number of plots across treatment and control farmers in a way that can only reduce the treatment effect.

We show in Table A14 that while conservatively trimming the sample in this way decreases the main coefficients of interest, the estimates remain statistically

[29] We show in Table A12 that the plots cultivated with Swarna-Sub1 were on average smaller, more likely to be land that was owned by the farmer rather than sharecropped and *less* likely to be on the lowest land in the village. However, Table A13 shows that the plots *not cultivated* with Swarna-Sub1 are roughly similar on these observables. A plausible explanation that reconciles these two results is that minikit recipients cultivated more plots as a result of obtaining the new technology. While those new plots were on average different than the other plots, this does not affect the remaining non-Swarna-Sub1 plots.

significant at least at the 10 percent level. This provides suggestive evidence that the comparison of non-Swarna-Sub1 plots across treatment and control farmers is not being driven entirely by plot selection.

B. *Changes in Mean Yield Rather than Variance*

The technology we study decreases downside risk without affecting yield during "good years" when flooding is absent. As a result, the technology both decreases the variance in output and increases mean yield. One potential explanation of our findings is that they could be driven by this income effect where the expectation of increased output at the end of the season changes agricultural decision making. The ideal experiment to decompose between these two channels would involve promising compensation to control farmers in the amount equal to the gain in expected output from Swarna-Sub1. This gain in expected output depends on both the yield advantage of Swarna-Sub1 and the total land area cultivated with it. It is important to note that compensating control farmers before planting in the amount equal to the expected output gain is likely conservative because of discounting, the increased certainty of compensation relative to uncertain productivity gains in the treatment group, and the liquidity value of having additional capital before planting.

We exploit natural variation in our data to simulate an experiment where compensation is provided before planting. During the first year of the study there was spatial variation in the intensity of flooding, even within fairly small geographic areas. We use this variation to generate a measure of the flood shock (or lack thereof) that would have been equivalent to the gain in expected output caused by Swarna-Sub1. Our calculation in Section IIID suggested that an upper-bound estimate for the purely agronomic gain of Swarna-Sub1 was 380 kg per hectare. Combining this with the fact that treatment farmers cultivated an average of 0.33 hectares with Swarna-Sub1 during the second year, the required compensation to turn off the expected output channel would be equivalent to 126.7 kilograms of rice. Table A15 shows that an additional day of flood exposure during the first year caused the total production of control farmers to decrease by 90.3 kg. Therefore, a decrease in flood exposure by 1.4 days is equivalent to the expected output gain from Swarna-Sub1. If our results are entirely driven by the mean-increasing property of the technology, then we would expect the effects of being exposed to 1.4 fewer flood days for control farmers to be equivalent to our measured effects of giving the new technology.

The results do not appear to be entirely driven by the mean-increasing property of Swarna-Sub1. Table A16 compares the main effects of the Swarna-Sub1 treatment with the effects of an equivalent flood shock in the control group—which is the farmer's area-weighted flood exposure divided by 1.4. Total fertilizer expenditure is the only outcome that decreases significantly with an additional 1.4 days of flood exposure. However, the negative effect of an additional 1.4 days of flooding is around one-fifth the size of the effect of the Swarna-Sub1 treatment. While this test is imperfect because it relies on nonexperimental variation, the results are mostly inconsistent with our results being driven by how the technology shifts the mean level of output.

C. *Other Alternative Explanations*

An additional potential income effect is that cultivation of the new seed variety during year one led to a boost in agricultural income which then crowded in improved inputs and practices during the following year. Our results do not appear consistent with this explanation for two reasons. First, the fact that we observe moderate impacts immediately during year one suggests that wealth effects from crop output during year one do not entirely explain our results during year two. Second, as another piece of evidence, we use data on the total quantity of rice harvested during the first year as a measure of the wealth that would have been influenced by being treated. If increases in wealth due to the new technology led to the changes we observe during year two, then controlling for the year one harvest should attenuate our main estimates. We show in Table A17 that none of our main estimates are affected when conditioning on the year one total harvest.

Are differences in output prices responsible for our results? We collected information on prices received by variety from each farmer that sold any output after the second year of the study. The average price received for Swarna was 10.29 Rs per kilogram and the average price received for Swarna-Sub1 was 10.76.[30] This 4.6 percent difference in prices is statistically significant at the 5 percent level. Since the eating quality of the two varieties is similar (see Figure A1), this difference in prices could possibly be due to increased value of output as seed rather than grain for consumption.

There is no evidence that output prices drive the results. Descriptively, only 40 percent of farmers sold any rice following the second year and on average only 17 percent of the harvest was sold as grain for consumption, suggesting that effects of output price differences are likely to be small. We consider this possibility further by separate estimation of the main results for the subsample of farmers that did not sell *any* rice following the second year.[31] If prices are explaining the results, then the effects of the technology should be smaller in this subsample. We show in Table A18 that this is not the case. This evidence is not consistent with output prices being the relevant channel for our results.

V. Conclusions

This paper has shown that technological progress in agriculture can have the important effect of crowding in the use of both more productive cultivation practices and modern inputs. This suggests that lack of more productive and resilient technology can be at least a partial reason why smallholder farmers in developing countries often fail to adopt improved production practices and use few modern

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[30] The government's paddy procurement program set the minimum support price (MSP) for the 2012 harvest at 12.5 Rs per kilogram. Many farmers in our sample sell instead to private traders at prices below this level.

[31] A problem with this approach is that the sample is being split according to an endogenous outcome. The most plausible effect of sample selection in this case is that the group of farmers selling rice are the largest and wealthiest farmers who have the most capacity to respond after having access to Swarna-Sub1. For instance, average landholdings of farmers that do not sell output are 50 percent less than the landholdings of those selling output. This would then work against us finding any effects in the subsample of farmers not selling output.

inputs. We have focused on new rice varieties that reduce downside risk through enhanced flood tolerance.

Additional calculations suggested that much of the gains from these new technologies come from this crowding-in effect. By inducing more use of a labor-intensive planting method, increased investments in fertilizer, increased uptake of credit, and displacing traditional seed varieties, technology boosts productivity. Put differently, the absence of seed varieties that are well adapted to local conditions causes farmers to opt for traditional low-input and low-productivity cultivation strategies. Our best estimate indicates that no less than 43 percent of the expected productivity gains from seed varieties that reduce downside risk can be attributed to crowd-in effects.

These results provide the first evidence on how technological progress that reduces downside risk in agriculture can modernize farming in areas where production risk is high. While the technology in our experiment has already been adopted by around 3 million farmers in India alone (Ismail et al. 2013), technological progress that makes seed varieties more tolerant to weather extremes is not unique to India. Since 2011, new rice varieties that are tolerant to either flooding, drought, or extreme cold temperatures have been released in 11 countries in South Asia and Africa alone.

These results suggest that efforts to improve technology by reducing the susceptibility of commonly used crop varieties to weather extremes can go a long way in increasing agricultural productivity. While the Green Revolution was successful at increasing agricultural productivity in favorable areas throughout the world, productivity in rainfed areas under weather stress remains low. Using flood tolerance as an example, we have shown that technological advances that improve resilience to climatic events can further enhance agricultural productivity by causing farmers to reoptimize their production practices. Not accounting for this reoptimization as a result of technological change leads to a large underestimation of the return from investing in research and development in agriculture.

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