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ORIGINAL ARTICLE

Measuring the impact of stress-tolerant rice variety adoption: Evidence on input use and yield in Nepal

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Abstract

New agricultural technologies, such as stress-tolerant rice varieties (STRVs), that reduce yield risk can modify farmers' production decisions. This article explores how STRV adoption affects farmer decision-making and productivity in Nepal in a non-drought year. STRVs are bred to be high-yielding and tolerant to climate shocks such as drought. To assess the effect of input measurements on treatment effects, we collected information from 900 households on STRV adoption and input use. We also conducted a survey experiment in which half of sampled households were randomly assigned to answer additional, more detailed questions on agricultural inputs. Farmers apply more total chemical fertilizer, pesticides, early-season chemical fertilizer, and land preparation labor to plots planted with STRVs compared to traditional varieties (TVs). Detailed input data enhances our understanding of how this "crowding-in" effect of STRV adoption on input use compares with other high-yielding varieties. While farmers increase application of a subset of these inputs on other improved variety types such as hybrids, results suggest that crowd-in effects are most consistent for STRVs. In the absence of drought, STRVs also provide a similar yield boost and yield variance reduction over TVs compared to other, non-stress tolerant improved varieties. Results suggest that improved varietal adoption, and STRV adoption in particular, can improve household productivity and modernization of agriculture.

KEYWORDS

climate-smart agriculture, farmer decision-making, inputs, Nepal, stress-tolerant rice varieties, survey design

JEL CLASSIFICATION

O13, Q12, Q16, Q54

1 INTRODUCTION

Farmer decision-making is a complex process. Each farm household must consider its income-generating opportunities, marginal productivity of inputs, and risk exposure, among other factors, when evaluating the potential costs and returns of a farming decision. New agricultural technologies can alter these factors, potentially affecting production decisions.

This article explores how adoption of a new agricultural technology affects farmer decision-making regarding input use, crop yield, and yield variance. It also addresses the level of detail on input application measurement needed to determine the impacts of technology adoption on decision making and outcomes. To answer these questions, we examine the adoption of stress-tolerant rice varieties (STRVs) in the Western Development Region of Nepal. STRVs are high-yielding modern varieties (MVs) bred to reduce yield losses during times of weather stress.

This article examines whether adoption of STRVs leads to "crowd-in" effects of agricultural inputs and impacts yield mean and variance. Although we collected data in a non-drought year, at the start of the season farmers allocate early-season inputs and labor based on future yield expectations. Therefore, we theorize that farmers apply more early-season inputs and labor to STRV plots compared to plots planted with traditional varieties (TVs) and other types of improved varieties, largely because of their reduced risk of yield loss.

In the study region, many households cultivate numerous plots and plant multiple varieties within each plot. This article controls for household and plot-level unobserved heterogeneity by taking advantage of the panel structure of the data and estimating correlated random effects (CRE) models. CRE models eliminate unobserved heterogeneity under certain assumptions, much like fixed effects models; this is crucial as we use observational rather than randomized experimental data on adoption. During data collection, we conducted a survey-design experiment. Half of respondents were randomly assigned an additional module that included detailed questions on agricultural inputs to examine the effect of input measurements on the estimated impacts of STRV adoption. This provides insights into the value of collecting detailed input data, which is costly in terms of survey enumeration and can contribute to respondent fatigue (Ambler et al., 2021).

Our results indicate that adoption of STRV and other improved varieties crowds in input use. Farmers apply more early-season fertilizer, land preparation labor, chemical fertilizer, and pesticides to plots planted with STRVs compared to plots planted with TVs. They also apply more land preparation labor to other MVs, more chemical fertilizer to other MVs and hybrids, and more pesticides to hybrids compared with TVs. This suggests that while all improved varieties crowd in input use, the effect is strongest for STRVs across more inputs, particularly early season inputs. We also find that even in a non-stress year, STRVs provide a yield boost and reduction in yield variance over TVs that are comparable to other newly released MVs. While variance reduction of STRVs is similar to that of hybrids, hybrids provide the highest overall yields.

Most literature on STRVs focuses on their impacts on productivity and measures of household well-being, rather than agricultural decisions. Studies conducted in sub-Saharan Africa found that the adoption of a drought-tolerant maize variety (DTMV) increases maize yields, market participation, and farm income among other positive outcomes while reducing yield variance and exposure to downside risk (Amondo et al., 2019; Katengeza & Holden, 2021; Makate et al., 2017; Martey et al., 2020; Simtowe et al., 2019; Wossen et al., 2017). Literature from Bangladesh and India found that drought-tolerant rice adoption increases yields in drought and non-drought years (Dar et al., 2020; Rahman et al., 2022). By contrast, Yamano et al. (2018) found yields of a drought-tolerant rice variety, also in India, to be lower than other varieties, even in drought conditions.

Two recent studies examine how stress-tolerant crops impact farmer decision making and outcomes. Emerick et al. (2016) found that farmers who were given a flood-tolerant STRV applied more fertilizer and used a more labor-intensive planting method compared to other farmers; they also cultivated more area under rice than farmers who did not receive an STRV. The STRV also had higher yields compared to a similar variety that lacked the flood-tolerance trait by 10 percent in the non-flood year, which the authors attributed entirely to the crowd-in effect, and by 14 percent in the flood year which they partially attributed to the crowd-in effect. The authors argued that when evaluating the returns on investment in stress-tolerant crops, it is crucial to consider the "crowd-in" effect as it enhances productivity regardless of climate shocks.

Simtowe et al. (2019) followed Emerick et al. (2016)'s conceptual framework to examine the impacts of DTMV adoption in Uganda and found that DTMV adoption increased yield while reducing yield variance and the probability of crop failure. Adoption also increased the area planted with maize, reduced the recycling of maize seed, and increased the use of mechanized tools, but did not influence input use or the probability of hiring labor.

We contribute to the literature on how new agricultural technologies, specifically STRVs, can help modernize agriculture in developing countries by crowding in input use. Our first contribution is to explore this topic in a new context as to our knowledge only two studies examine the crowd-in effects of STRVs (Emerick et al., 2016; Simtowe

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et al., 2019). In contrast to the study area of Emerick et al. (2016), the major climate risk in the Western Development Region of Nepal is drought rather than flood. Between 2001 and 2010, droughts in Nepal resulted in economic losses of $753 million for paddy alone; 2006 was a particularly bad year when drought reduced rice yield by 11% (MoFE, 2021). We examine the impacts of ten STRVs that have been cultivated by farmers in this region for several years, nine of which are drought-tolerant. By contrast, Emerick et al. (2016) examined a recently introduced flood-tolerant variety, and Simtowe et al. (2019) estimated the impact of a different crop (maize).

Our second contribution is to explore the productivity effects (yield and yield variance) of STRVs in a non-stress year. STRVs likely have larger productivity boosts compared to other variety types during times of stress. However, if improved performance during times of stress is paired with poor performance during normal years, this could hamper adoption efforts. Previous literature has found this to be the case for another climate-smart technology, conservation agriculture (CA) (Michler et al., 2019). The authors found that across multiple crops in Zimbabwe, CA generally leads to no yield gain, and sometimes yield losses, in normal growing years. They conclude that this may contribute to low adoption in sub-Saharan Africa. In the case of STRVs in Nepal, the yield benefits during a normal, non-stress growing year are encouraging for continued adoption.

Farmers in our study region grow a wide range of rice variety types including TVs, STRVs, other (non-STRV) MVs, and hybrids. This allows us to compare farmer decision-making and productivity across different variety types, and thus draw conclusions as to the relative benefits of STRVs compared to other MVs and hybrids. This is important because farmers can choose between any of these variety types; the relative yield and yield variance of these varieties during a non-stress year are crucial in influencing adoption patterns. Furthermore, information on the crowd-in effects of STRVs versus other MVs and hybrids may inform research, development, and promotion of new rice varieties. Focusing on STRVs in particular is important because of their additional risk-reducing properties and the productivity benefits they offer during times of climate stress.

Our third contribution is to provide evidence on the importance of collecting detailed input data when designing surveys to assess the impacts of new technologies by randomizing an additional input module. Response fatigue occurs during data collection and can affect data quality (Ambler et al., 2021). Ambler et al. (2021) call for research to explore trade-offs between more detailed data and the risk of inducing fatigue to guide researchers. We find that having detailed information on the timing of fertilizer applications and breakdown of labor data by task is crucial for understanding how STRVs impact farmer decision-making.

The next section of the article describes our study area and data. Section 3 explains our conceptual framework and Section 4 details our empirical models. Descriptive statistics are provided in Section 5 and econometric results are provided in Section 6. Finally, Section 7 provides concluding remarks.

2 | BACKGROUND AND DATA

This study was conducted in the Lamjung, Tanahu, and Gorkha districts of the Western Development Region of Nepal. Rice, the most important local crop, is mainly grown during the monsoon season between June and November. Some farmers in these districts have access to irrigation but many rely on rainfed cultivation. Landholdings in this region are small, and mechanization is lacking (Adhikari & Tripathi, 2017).

Research has found that the frequency and intensity of drought have been increasing over the past few decades in several areas of Nepal, including some areas of the Western Development Region (Bagale et al., 2021). The study area has a relatively high level of average annual precipitation compared to other regions of Nepal, and it was in a region with no or mild drought in 2018 (Bagale et al., 2021; Baniya et al., 2019). However, drought has occurred in this region in prior years[1], such as in 2005 and 2015, and is a risk to producers (Bagale et al., 2021; Gauchan et al., 2012).

Before 2005, the drought-prone Western Development Region of Nepal lacked STRVs that were well-suited to the region, and farmers had limited access to quality seeds (Adhikari & Tripathi, 2017). To address these issues, national and international organizations collaborated between 2005 and 2008 to identify and release STRVs. The STRVs were validated using participatory variety selection. Seed producer groups (SPGs) were then established to facilitate the multiplication and sales of the recently validated STRVs. Since then, adoption of the varieties has been widespread in the districts in which the SPGs operate. Adoption is higher on average in villages that contain an SPG or are very near to a village with an SPG compared

[1] Based on weather data between 1971 and 2019, the drought risk is considered very high in Gorkha district and low in Lamjung and Tanahu districts (MoEF., 2021). Our study area encompasses small areas of Gorkha, Lamjung, and Tanahu districts, where the areas in Lamjung and Tanahu districts are near Gorkha district (Figure 1). Given the important drought spatial variabilities within districts (Bagale et al., 2021) and that this area was identified as drought-prone by national and international organizations, evidence suggests that drought is a risk to rice farmers in our study area.

to villages that are a greater distance from an SPG. This suggests that the SPGs have been effective in promoting and spreading the varieties (Vaiknoras & Larochelle, 2023). Farmers can access seed via the SPGs, or through private seed dealers or district extension offices.

Ten STRVs are grown in this region: nine are drought-tolerant and one is flood-tolerant (these are listed in Table A1). Farmers in this region also grow TVs which are low-yielding; other, non-STRV MVs which are higher-yielding but lack stress tolerance; and hybrids which are the highest-yielding varieties but have higher seed costs and lack stress tolerance (Crop Development Directorate, 2015). MVs in Nepal are often classified as old-generation MVs, released from the 1960s to 1980s, or new-generation MVs released after 1990 (Crop Development Directorate, 2015; Gauchan et al., 2012).

This area was chosen for this study to examine the effects that the SPGs and STRVs have had on local households (Vaiknoras & Larochelle, 2023). As of 2015, adoption of STRVs was low in the Western Development Region as well as nationally: individual STRVs were estimated to cover less than 1% of rice area in most regions. Comparatively, it was estimated that old MVs covered 51 percent of rice area and new MVs collectively covered 41 percent of rice area (Crop Development Directorate, 2015). However, in 2018 STRV adoption was much higher in the study area: between 35% and 60% of non-SPG members had grown an STRV in at least one season, depending on proximity to an SPG (Vaiknoras & Larochelle, 2023).

Household survey data were collected in 75 villages in Lamjung, Tanahu, and Gorkha districts during November–December of 2018. The villages were selected from the study area represented by the yellow area in Figure 1. The study area was defined to include Village Development Committees[2] (VDCs) where STRVs have been heavily multiplied and sold via the established SPGs. Respondents from 12 randomly selected households were interviewed in each of the 75 villages for a total of 900 households. The survey collected information on rice cultivation during the 2018 monsoon season using four modules: three were administered to all households and one was administered to half of households. The first module (administered to all households) identified each rice variety grown by the household in that season. Each variety was classified as a TV, old MV (released in 1990 or earlier), non-STRV new MV (released after 1990), STRV, or hybrid variety.

It is crucial for our study that respondents accurately identify the rice varieties they cultivated in 2018. Before the household survey was conducted, the researchers interviewed extension agents, seed dealers, and other experts regarding farmers' knowledge of rice variety names and ability to identify what they grow. These interviews yielded a consensus that farmers are aware of the official names of varieties they cultivate, particularly newer varieties such as the STRVs, and especially hybrids. TVs, however, may have different local names depending on the village. To help with varietal identification during data collection, a list of variety names was prepared using information from interviewed experts, leaders of the local SPGs, and other varietal documentation (Crop Development Directorate, 2015). For the few cases in which farmers reported varieties that were not on this list, local experts helped classify whether they were TV, old or new MV, STRV, or hybrid.

The second module (administered to all households) collected information on each plot that the household cultivated that season, including plot size and characteristics. For plots planted with rice, additional questions on inputs were asked. Questions on labor covered the number of people who worked on the plot, average number of days worked per person, and average hours worked per day. For these questions, respondents were asked to consider all tasks for rice production on the plot (from nursery and land preparation to threshing) and report total labor for these tasks combined. This module also collected data on the quantity of fertilizer and pesticides applied.

In each village, six households were randomly selected[3] and administered the third module which contained detailed plot-level questions on labor and input use immediately after the other input module. The labor questions included the number of paid and unpaid person-days by gender spent on the following tasks: (i) nursery, land preparation, and planting; (ii) weeding and pest control; (iii) harvesting; and (iv) threshing. The additional module also included detailed questions on fertilizer (chemical and organic) and pesticide application, that is, the number of applications, the day in the season this occurred (with day 0 being the day of transplanting the rice seedlings), quantity per application, and the type when applicable (DAP, potash, and urea for chemical fertilizer; herbicide, fungicide, or insecticide for pesticides).

Finally, a fourth module (administered to all households) linked the rice varieties cultivated by the household (first rice module) to rice plots (second and third rice modules when applicable) to create a pseudo-panel data structure where some households have multiple plots, and some plots have multiple varieties. Questions in this module asked for the quantity of seed for *each variety* planted on the specific plot, the land area allocated to each vari-

[2] A VDC is an administrative unit larger than villages but smaller than districts.

[3] We test whether several household characteristics differ between assignment groups and find no statistical differences between assignment groups, indicating that the randomization was successful (table A2).

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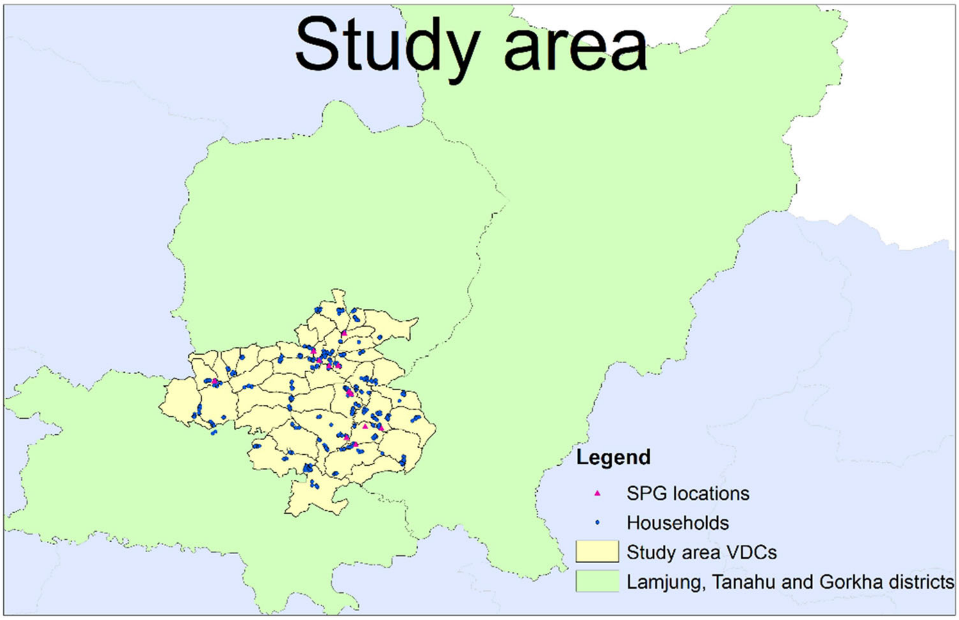

FIGURE 1 Map of Lamjung, Tanahu, and Gorkha districts showing study area.

ety on that plot, and the quantity of grain harvested for each variety on the plot. This information allows calculation of the seeding rate and yield at the variety-plot level (e.g., yield of variety 1 cultivated on the plot). For each variety planted on each plot, farmers also reported the age of seedlings on the day of transplantation. Plots were identified as contiguous parcels of land on which the same level of inputs was applied.

3 | CONCEPTUAL FRAMEWORK AND HYPOTHESES

We adapt the conceptual framework developed by Emerick et al. (2016) which explains STRV crowd-in effects via three mechanisms. The first is the *income effect*: the STRV provides higher expected yields and incomes than a non-STRV variety because, in the case of stress, yield loss is lower. The second is the *marginal productivity effect*: STRVs reduce yield losses during a stress year, increasing the expected marginal productivity of inputs on average. Finally, the third mechanism is the *downside risk effect*: investing in inputs is less risky because of the lower risk of total crop failure. The authors argue that the *downside risk effect* of STRVs is the most important mechanism for crowding in input use.

We expand this conceptual framework to consider how each improved variety type grown in our study area (STRV, new MV, old MV, and hybrid) may crowd in inputs compared to a TV. Consider the following simplified equation for expected yield (E[Y]), where Ø is the farmer's expected probability that a climate stress event (e.g., drought or flood) will occur during the growing season:

$$E\ [Y] = \emptyset(E[Y|stress]) + (1 - \emptyset)\,(E[Y|nonstress]) \quad (1)$$

$E[Y]$ is a function of the expected yield potential of a specific variety type during both stress and non-stress years, conditional on input use, and other factors such as plot characteristics. Because improved varieties are generally bred to be high-yielding and more responsive to inputs, the *income effect* and *marginal productivity effect* may cause the crowding in of inputs for all improved variety types compared to TVs. However, these effects may be stronger for STRVs because their expected yield is higher than all other improved varieties in a stress year, boosting the overall expected yield, $E[Y]$. STRVs have the additional benefit of reducing risk, thus generating the *downside risk* effect. Any factor that increases the farmers' perceived risk of drought, including how drought-prone their region is, could alter the strength of the downside risk effect and thus the strength of the crowd-in effects: the greater the risk of drought, the greater the crowd-in effects should be. In addition, if farmers are loss-averse then the downside risk effect could be particularly strong.

In a nonstress year, theta is highest at the start of the season and declines as the season progresses, approaching zero at harvest time. Therefore, crowd-in effects for STRVs, relative to other improved variety types, should be strongest at the start of the season.

3.1 | Hypotheses

We form our study hypotheses knowing that 2018 was not a stress year for farmers in our study area.[4] Our first hypothesis is that farmers will apply more inputs to all improved variety plots compared to TV plots. This is because as the season continues and the chance of climate shock declines, the *downside risk effect* declines in importance while the *income* and *marginal productivity effects* remain.

Our second hypothesis is that farmers will apply more early-season inputs on plots planted with STRVs compared to plots planted with TVs, due to a combination of the *income*, *marginal productivity*, and *downside risk effects*. We expect smaller (or no) crowd-in effects of early-season inputs on plots planted with other improved varieties because these varieties offer no protection against risk. However, they are still expected to provide a higher income and marginal productivity of inputs compared to TVs.

Finally, we hypothesize that STRVs, other MVs, and hybrids will achieve higher yields in a non-stress year than TVs because of their high-yielding properties and crowd-in effects. Due to differences in moisture availability within the area even in a non-stress year, we expect STRVs to have a lower yield variance, on average, than TVs.

4 | Empirical models

In this section, we first introduce empirical models used to examine crowd-in effects and productivity gains from adopting STRVs and other improved varieties. We then explain our model assumptions.

4.1 | Input models

To test our hypotheses, we take advantage of the fact that households have multiple rice plots leading to a pseudo-panel data structure by estimating CRE models. To examine the crowd-in effect of STRV adoption and the adoption of other improved varieties by household i on plot j, we estimate the following model:

$$\boldsymbol{O_{ij}} = \beta_0 + \boldsymbol{\beta}_1 \boldsymbol{T_{ij}} + \boldsymbol{\beta}_2 \boldsymbol{P_{ij}} + \boldsymbol{\beta}_3 \boldsymbol{H_i} + \boldsymbol{\pi}_1 \overline{\boldsymbol{T_i}} + \boldsymbol{\pi}_2 \overline{\boldsymbol{P_i}} + \mu_i + c_{ij} \tag{2}$$

The outcome indicators represented by the vector $\boldsymbol{O_{ij}}$ include input measures computed from the standard input module, to which all households responded, and the additional input module, completed by about half of the sample. The inputs from the standard module are the quantity of organic fertilizer (kg/ha), chemical fertilizer (kg/ha), pesticides (L/ha), and labor (person-days/ha). The input measures from the additional input module are the quantity of chemical fertilizer (kg/ha) applied before or at the day of transplantation and labor devoted to land preparation (person-days/ha). All labor variables include hired and unpaid labor.

$\boldsymbol{T_{ij}}$ is a vector of treatment dummy variables for rice variety types: old MV, new MV, STRV, and hybrid, with TVs as the reference category. For plots planted with more than one variety, $\boldsymbol{T_{ij}}$ represents the variety type for which the greatest quantity of seed was planted on the plot[5]. We control for the following plot characteristics ($\boldsymbol{P_{ij}}$) that may be correlated with both adoption and input outcomes to reduce plot-level selection bias: plot size (ha) and dummy variables for plot slope (0 = flat; 1 = sloped), whether the plot is susceptible to drought as reported by the farmer (1 = yes), and is irrigated (1 = yes). Household-level variables ($\boldsymbol{H_i}$) include household head sex (1 = female) and literacy (1 = literate), elevation of the dwelling in meters above sea level (masl), and a dummy variable equal to one if the household resides in a village where there is an SPG that sold STRV and other improved rice seed to local farmers. SPGs have been found to increase adoption of STRVs and usage of some best management practices, which could affect the outcomes of interest (Vaiknoras & Larochelle, 2023). Variable descriptions are presented in Table A2.

For households with multiple plots, we include plot averages for all variables included in the vectors $\boldsymbol{T_{ij}}$ and $\boldsymbol{P_{ij}}$, and denote these vectors as $\overline{\boldsymbol{T_i}}$ and $\overline{\boldsymbol{P_i}}$. This isolates the within-household effects of these variables (e.g., the effect of adopting an STRV for a given household), captured by $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$, from the between effects (e.g., the difference between households that do and do not grow an STRV variety) (Schunck, 2013). The $\boldsymbol{\pi}$ coefficients measure the difference between the within and between effects of adoption (Antonakis et al, 2021). The within-household treatment effect $\boldsymbol{\beta}_1$ is our treatment effect of interest. By isolating the within-household effects of $\boldsymbol{T_{ij}}$, the CRE model eliminates unobserved household-level heterogeneity from $\boldsymbol{\beta}_1$, including household-level selection bias. This also eliminates any potential spillover effects of STRV adoption in which planting an STRV on one plot would induce households to increase input applications

[4] When asked if households experienced drought in the past five years, and what the three worst drought years had been, only 16 households in total named 2018 as a top three drought year. This is consistent with Bagale et al (2021) which shows our survey area being classified as "no drought" or "mild drought" in 2018.

[5] We also estimate the input crowd-in effect models on the subsample of plots planted with only one variety as a sensitivity check to ensure that results are not being driven by additional variety types on the plot.

on all plots. Bias could remain from plot selection at the household level; this is discussed further in section 4.3.

The residual error is split into two error components, unobserved heterogeneity that varies across households (μ_i), such as farmer ability, and unobserved heterogeneity that varies across plots (c_{ij}), such as unobserved soil quality.

4.2 | Yield models

We estimate the following model to investigate the effect of STRV and other improved variety adoption on yield (measured as paddy yield) and yield variability ($\boldsymbol{Y_{ijk}}$) of variety k on plot j by household i:

$$\boldsymbol{Y_{ijk}} = \beta_0 + \boldsymbol{\beta}_1\boldsymbol{T_{ijk}} + \boldsymbol{\beta}_2\boldsymbol{S_{ijk}} + \boldsymbol{\beta}_4\boldsymbol{P_{ij}} + \boldsymbol{\beta}_5\boldsymbol{H_i} + \boldsymbol{\pi}_1\overline{\boldsymbol{T_{ij}}} + \boldsymbol{\pi}_2\overline{\boldsymbol{S_{ij}}} + \boldsymbol{\pi}_4\overline{\boldsymbol{P_i}} + \mu_i + c_{ij} + v_{ijk} \tag{3}$$

Each combination of i, j, and k is unique, meaning that if household i grew two varieties on plot j, there are two observations. Similarly, if household i grew variety k on two plots, they are treated as two observations. Yield (kg/ha) of variety k harvested on plot j enters the model in the logarithmic form. Yield variability is measured over space following the moment-based approach developed by Antle (1983) and estimation procedures described by Wossen et al. (2017). Estimation errors from the yield regression are computed by subtracting the predicted outcome value from the actual outcome value. We then square these errors and use them as the dependent variable.

The treatment variable $\boldsymbol{T_{ijk}}$ is the type of variety k grown on plot j by household i, where the reference category is TVs as in Equation (2). Similarly, $\boldsymbol{P_{ij}}$ and $\boldsymbol{H_i}$ represent plot and household characteristics as defined above. $\boldsymbol{S_{ijk}}$ includes variables related to variety k grown on plot j by household i: the seeding rate (the quantity of seeds of variety k planted in kg divided by plot j's area allocated to variety k in hectares) and age of seedlings in days on the day of transplantation. These are included because SPG members were trained to lower seeding rates and the age of seedlings at the time of transplantation compared to common local practices, and these could impact yield.

Equation (3) includes $\overline{\boldsymbol{P_i}}$, a vector of plot characteristics averaged at the household-level as in Equation (2), and $\overline{\boldsymbol{T_{ij}}}$ and $\overline{\boldsymbol{S_{ij}}}$ which are plot-level means for varietal adoption and seed characteristics. This isolates the within-plot effects of these variables (e.g., the effect of a household planting an STRV on a given plot) (Schunck, 2013). Where $\boldsymbol{\beta}_1$ in Equation (2) is free from unobserved household-level heterogeneity, $\boldsymbol{\beta}_1$ in Equation (3) is free from unobserved household and plot-level heterogeneity.

The error term is split into three components: μ_i and c_{ij} which represent the household and plot-level unobserved heterogeneity as in Equation (2), and v_{ijk} which is the unobserved heterogeneity at the variety-plot-household level. This could include unobserved factors such as seed quality.

4.2.1 | Capturing the effect of inputs on yields

Because we assume that input use is likely endogenous in Equation (3), we do not include any input-related variables. However, we are interested in the effect of input use on productivity. We want to determine whether crowd-in effects boost the productivity of STRVs and whether including input covariates measured at the granular level influences the magnitude of the treatment effects. We thus re-estimate the yield regressions using random effect (RE) models because the CRE model eliminates plot-level heterogeneity:

$$\boldsymbol{Y_{ijk}} = \beta_0 + \boldsymbol{\beta}_1\boldsymbol{T_{ijk}} + \boldsymbol{\beta}_2\boldsymbol{S_{ijk}} + \boldsymbol{\beta}_3\boldsymbol{I^l_{ij}} + \boldsymbol{\beta}_4\boldsymbol{P_{ij}} + \boldsymbol{\beta}_5\boldsymbol{H_i} + \mu_i + c_{ij} + v_{ijk} \tag{4}$$

$\boldsymbol{I^l_{ij}}$ is a vector of inputs applied on plot j that varies over the superscript l. When $l = 0$, the vector does not include any input variables. When $l = 1$, the vector includes input variables computed from the standard input module (Table A2). When $l = 2$, inputs are measured from the additional detailed input module (Table A2). Equation (4) is estimated for $l = 0$, $l = 1$, and $l = 2$.

If the inclusion of the endogenous inputs reduces the magnitude of $\boldsymbol{\beta}_1$ coefficients, it suggests that the crowd-in effects contribute to the productivity gain of improved varieties (Emerick et al., 2016). To examine how input measurements influence the estimated productivity gain, we re-estimate the yield regressions using only households who were administered the detailed input module for $l = 1$ and $l = 2$ and then compare $\boldsymbol{\beta}_1$. Given that the input variables are endogenous, the coefficients cannot be interpreted as causal and are useful for comparisons only.

4.3 | Model assumptions and limitations

CRE models function like fixed effects (FE) models to eliminate much of the potential endogeneity that can bias the estimation of treatment effects (Schunck, 2013). This is important, as the decision to adopt an STRV is not random; thus, we use the CRE models to reduce the likelihood of selection bias in our results. The benefit of CRE models over FE models is that they estimate coefficients for variables with no within-group variation (Schunck, 2013). However, estimating unbiased treatment effects from models (2) and (3) (i.e., the crowd-in effect and yield effect of STRV adoption, respectively) requires a few assumptions.

In Equation (2), c_{ij} must remain uncorrelated with $\boldsymbol{T_{ij}}$, meaning that there are no unobserved plot-level characteristics that correlate with production practices and varietal choice. This assumption may not hold if households target STRVs to plots with unobserved characteristics and would bias $\boldsymbol{\beta}_1$ upward. In addition, because our data are not balanced (i.e., not all households cultivate the same number of plots), the number of per-household plot observations must also be uncorrelated with c_{ij} (Wooldridge, 2010). In Equation (3), $\boldsymbol{T_{ijk}}$ must be uncorrelated with v_{ijk}. This correlation could arise if there are unobserved variety-plot level traits correlated with yield and variety type, such as the quality of seed planted to a plot. Here, because not all plots have the same number of varieties, the number of variety observations must also be uncorrelated with v_{ijk} (Wooldridge, 2010). We include variables at the variety-plot level (seeding rate and age of seedlings) and several plot characteristics to minimize these correlations.

Another assumption is that there is no reverse causality. This means that farmers must first decide what variety to plant, and then decide what production practices to follow, rather than vice-versa. There is no approach to test this assumption. We believe it makes intuitive sense that farmers choose production practices based on variety type, rather than choose variety type based on production practices.

A limitation of CRE models is that the treatment effects estimations only use information for households (Equation 2) and plots (Equation 3) that have within-group variation (Schunck, 2013). To assess the severity of this limitation, we examine descriptively how characteristics vary across households with one versus more than one plot, and plots with one versus more than one variety. This provides some evidence as to whether the CRE model results are likely to be representative of the total household sample.

The RE model capturing the effect of inputs on yields (Equation 4) requires the more restrictive assumptions that adoption of STRVs cannot be correlated with unobserved household or plot-level heterogeneity, captured by μ_i and c_{ij}, respectively. In addition, the likely endogeneity of input application introduces bias into treatment effects. Thus, the results of the RE models are not to be interpreted causally but rather to shed light on how the inclusion of input variables changes the effect of adoption on productivity.

Our analysis is unable to account for heterogeneity in the effect of STRV adoption. $\boldsymbol{\beta}_1$ represents the average treatment effect across all STRV varieties, regardless of the specific variety or how many years the household has cultivated it. In reality, some STRVs may be higher-yielding than others, and early adopters may have had more experience with input applications and be more familiar with their risk-reducing properties, which can lead to greater crowd-in effects and yield gain compared to late adopters.

4.3.1 | The augmented regression test

In Equations (2) and (3), if $\boldsymbol{\pi}_1 = 0$, then the within-effects and between-effects are equivalent for the variety treatment variables, suggesting that there is no household-level (in Equation (2)) or plot-level (in Equation 3) selection bias of adoption. In this case, the RE model that is estimated without including the treatment-variable means ($\overline{\boldsymbol{T_i}}$ and $\overline{\boldsymbol{T_{ij}}}$) is more efficient and is not biased. We also test for $\boldsymbol{\pi}_1, \boldsymbol{\pi}_{2,}\ \boldsymbol{\pi}_4 = 0$ jointly. If $\boldsymbol{\pi}_2 = 0$ ($\boldsymbol{\pi}_4 = 0$) then the within-effects and between-effects for plot-level variables (seeding variables), other than variety type are equivalent (Schunck, 2013). While variety type is our treatment variable of interest, examining all $\boldsymbol{\pi}$ coefficients collectively provides some additional insight into selection bias.

5 | DESCRIPTIVE STATISTICS

In this section, we present descriptive statistics to provide important context for our econometric models and results. First, we provide some descriptive evidence that survey length was randomly assigned to households and compare input use between input module types. We then present descriptive statistics comparing variety types. Finally, we explore the distribution of the number of cultivated rice plots across households and cultivated varieties per plot.

5.1 | Survey randomization and input use by survey assignment

To determine whether survey length was assigned randomly to households, we compare households that received the detailed input module with those that did not (Table A3). We focus on characteristics that may have pushed enumerators to administer the standard shorter survey, such as those influencing difficulty reaching the household and interview length (e.g., number of cultivated plots). We find no statistical differences between assignment groups, indicating that the randomization was successful.

We compare data on input use from the two input modules to examine whether responses varied across modules

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TABLE 1 Input use by survey assignment and type of input module.

Variable	Responses from the standard input module: Households assigned to the standard input module (1) Mean (Std. dev.)	Responses from the standard input module: Households assigned the detailed input module (2) Mean (Std. dev.)	Responses from the detailed input module Households assigned the detailed input module (3) Mean (Std. dev.)
Organic fertilizer (kg/ha)	8682.94	8635.81	7974.79
	(10,046.27)	(9720.60)	(10,627.71)
Chemical fertilizer (kg/ha)	120.30	121.27	121.83
	(106.74)	(113.11)	(112.77)
Pesticides (L/ha)	.41	.38	.34
	(1.94)	(2.10)	(1.65)
Labor (person-days/ha)	619.06	576.67	323.59
	(575.95)	(488.53)	(193.98)***
Number of plot-level observations	660	544	544

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively, for a *t*-test of differences between columns 2 and 3. The organic fertilizer estimate is based on 1200 total observations while chemical fertilizer is based on 1199 observations due to missing responses. Column 2 summarizes responses to the standard input module questions for households who were also asked to respond to the additional, more detailed input module: detailed input module responses from these households are provided in column 3.

and randomized assignment groups. The responses from the standard input module did not vary statistically by assignment group (Table 1, columns 1 and 2)[6], suggesting further that survey assignment was random. When comparing the different modules, estimates of labor usage were significantly larger in the standard than in the detailed input module, while responses for other inputs did not vary statistically (Table 1, columns 1 and 3).

Previous literature argues that labor use may be more susceptible to recall bias than other inputs such as fertilizer because labor is used throughout the season while fertilizer is generally applied only a few times (Beegle et al., 2012). Because our detailed input module directed respondents to consider specific labor tasks, we hypothesize that labor estimates from the detailed input module may be more accurate.

5.2 | Input use, plot characteristics, and yield by variety type

We present descriptive statistics by variety types for the dependent variables and covariates included in our models. In total, 9% of plots had a TV as the dominant variety compared to 21% for old MVs, 27% for new MVs, 21% for STRVs, and 22% for hybrids (Table 2). Plots with STRVs are less likely to be irrigated and more likely to be prone to drought than other plots; they are also smaller and more likely to be sloped than some other types (significant at the 10% level or lower). This suggests that farmers consider plot characteristics when planting varieties, emphasizing the importance of controlling for plot characteristics.

Households applied more total labor, land preparation labor, total chemical fertilizer, and early-season chemical fertilizer to STRV plots on average compared to plots planted with TVs (Table 3) (significant at a 10% level or greater). Average input usage does not vary statistically between STRV and other types of improved varieties. The average yield of STRVs (4196 kg/ha) is significantly higher than that of TVs (2922 kg/ha), and lower than other variety types (significant at a 10% level or greater) (Figure 2). Table A1 shows the average yield of each STRV variety for which data were available, as well as their share of total STRV adoption.

[6] Although 50% of households should have received the long survey version, only 45% of households did. For 43 plot-level observations across 22 households, enumerators entered at the start of the survey that they would give the long version, but households did not answer the extended survey modules. We include these as short-survey observations so that we do not lose these observations; this does not affect the statistical similarity between the short-survey and long-survey groups of observations.

TABLE 2 Plot characteristics by variety type.

Variables	Plots planted with: TVs	Old MVs	New MVs	STRVs	Hybrids
Plot characteristics					
Irrigated (1 = yes)	.84	.92	.93	.70	.88
	(.37) ***	(.28) ***	(.26) ***	(.46)	(.33) ***
Prone to drought (1 = yes)	.57	.44	.44	.67	.47
	(.50) *	(.50) ***	(.50) ***	(.47)	(.50) ***
Slope (1 = yes)	.84	.65	.66	.79	.67
	(.37)	(.48) ***	(.47) ***	(.41)	(.47) ***
Plot size (ha)	.30	.27	.24	.22	.21
	(.37) ***	(.19) ***	(.16)	(.20)	(.17)
Number of plot observations (share of total)	110 (9%)	248 (21%)	326 (27%)	252 (21%)	262 (22%)

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively, for a test of difference of means from STRV plots. Standard deviations are reported in parentheses.

TABLE 3 Input use from standard and detailed input modules by variety types.

Variables	Plots planted with: TVs	Old MVs	New MVs	STRVs	Hybrids
Standard module inputs					
Labor (person-days/ha)	507.87	601.54	612.93	626.81	601.97
	(486.56) *	(443.86)	(579.46)	(580.66)	(548.36)
Organic fertilizer (kg/ha)	8085.14	8290.32	8142.87	9266.12	9372.56
	(11111.52)	(9791.40)	(9652.18)	(9940.20)	(9785.93)
Chemical fertilizer (kg/ha)	80.84	130.06	127.24	116.07	125.22
	(84.81) ***	(110.58)	(115.94)	(99.44)	(116.57)
Pesticides (L/ha)	.08	.40	.33	.49	.44
	(.45)	(1.91)	(1.44)	(2.70)	(2.03)
Number of plot observations (share of total)	110 (9%)	248 (21%)	326 (27%)	252 (21%)	262 (22%)
Detailed module inputs					
Early-season chemical fertilizer (kg/ha)	37.97	63.64	60.04	63.51	65.91
	(54.34) **	(70.83)	(60.03)	(59.76)	(82.64)
Land preparation labor (total, person-days/ha)	105.33	120.74	115.96	130.65	119.54
	(95.89)*	(84.16)	(86.31)	(92.48)	(82.73)
Number of plot observations	53 (10%)	125 (23%)	151 (28%)	103 (19%)	110 (20%)

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively, for a test of difference of means from STRV plots. Standard deviations are reported in parentheses. Swarna sub1, a submergence-tolerant variety, made up 6% of the STRV observations in our sample; 90% of observations for this variety were planted on irrigated plots and 30% on plots prone to drought.

Responses for standard module inputs come from all surveyed households while responses for detailed module inputs come from the fifty percent of surveyed households that were given the additional detailed input module.

5.3 | Plots per household and varieties per plot

Most households (69%)[7] in our survey cultivated one rice plot during the monsoon season in 2018; 27% cultivated two rice plots, and 4% cultivated more than one rice plot. Of the rice plots cultivated by households in our sample, about 75% were planted with one rice variety while 19% had two varieties, and 6% had more than two varieties. Because the CRE coefficients of interest are estimated using only within-group variation, they do not capture the information from all observations. Thus, we compare households (plots) with one plot (variety) to those with more than one to explore how representative they are of the full sample (Tables A4 and A5).

[7] Of households that grew an STRV in 2018, 15% also grew a TV, 19% grew an old MV, 31% grew another new MV, and 33% grew a hybrid variety. Of the plots that had an STRV, 8% also had a TV, 10% had an old MV, 11% had another new MV, and 13% had a hybrid variety.

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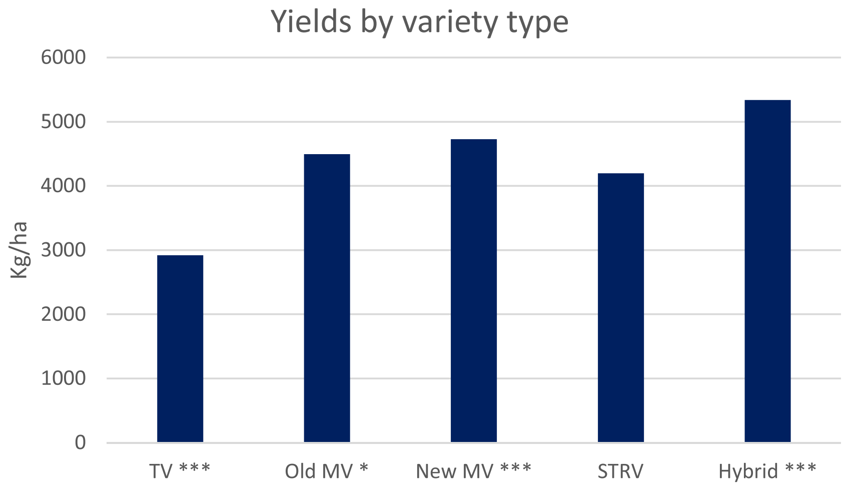

FIGURE 2 Yield by variety type.

Note: */**/*** denotes that the mean is different from that of STRVs at a 10%/5%/1% level of significance. The sample of varieties includes 235 TVs (14% of total), 307 old MVs (19%), 388 new MVs (24%), 232 STRVs (20%), and 381 hybrids (23%).

Households that cultivate more than one plot have more adults in the household, live farther from roads, and are more likely to live in a village with an SPG than those that cultivate one plot (significant at a 5% level) (Table A4). Plots with more than one variety are larger and less likely to be sloped than plots with only one variety (Table A5). They are also less likely to be rated as having a high level of soil quality.

These differences mean that CRE model results may not be representative of the total sample. Therefore, it is best to interpret CRE results as being representative of households that cultivate more than one plot and plots that have more than one variety on them.

6 | ECONOMETRICS RESULTS

6.1 | Crowd-in effects of STRV adoption

Table 4 presents within-household effects of improved varietal (STRV, old and new MV, and hybrid) adoption on full-season input use ($\boldsymbol{\beta}_1$ from Equation 2). While the null hypothesis that the variables in the $\boldsymbol{\pi}_1$ and $\boldsymbol{\pi}_2$ vectors are jointly equal to 0 is rejected for most regressions presented in Tables 4 and 5, the null hypothesis that $\boldsymbol{\pi}_1 = \mathbf{0}$ cannot be rejected for any of them. This suggests that, for our treatment variables, the within-household effects and between-household effects are equivalent and therefore the RE model is preferred. However, it also suggests that there is some selection bias for other plot-level variables such as slope or irrigation. Because we are primarily interested in the role of variety type, we place more importance on the test $\boldsymbol{\pi}_1 = \mathbf{0}$. In general, CRE results are more significant for STRVs than RE results and we present results for both (Table 4).

According to the preferred RE model results, households apply between 21 and 32 additional kg/ha of chemical fertilizer on plots cultivated with improved varieties compared to TVs (Table 4, column 6). A Wald test indicates that the magnitude of the chemical fertilizer coefficients is statistically equivalent across improved variety types. Households apply an additional .3–.4 L/ha of pesticides to plots planted with STRVs and hybrids (these results are statistically equivalent) compared to plots under TVs. Pesticide application on other MV plots was similar to that of TVs.

We next examine the effect of varietal selection on early-season fertilizer use and land preparation labor. RE models are again preferred based on augmented regression tests. These analyses are performed on the sub-sample of households that were randomly assigned to the detailed input module data. Households apply an additional 17 kg/ha of chemical fertilizer before or on the day of transplantation to STRV plots compared with TV plots (Table 5, column 2) (significant at a 5% level). An additional 22 person-days/ha of land preparation labor is devoted to STRV plots compared to TV plots (Table 5, column 4) (significant at a 5% level). The only early-season input significant at a 5% level or lower for other varieties is land preparation labor for old MVs: households apply an additional 24 person-days/ha to these plots compared to TVs. This is consistent with our hypothesis that early-season crowd-in effects are strongest for STRV plots compared to other improved varieties.[8]

[8] We also estimated crowd-in effects models on plots with only one variety type cultivated on them and our main results did not change.

TABLE 4 CRE and RE estimates of the effects of variety type on input use.

Variables	Labor (person-days/hectare)		Organic fertilizer (kg/hectare)		Chemical fertilizer (kg/hectare)		Pesticides (L/hectare)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T_{ij}	CRE	RE	CRE	RE	CRE	RE	CRE	RE
Variety type								
Old MV	20.203	21.338	239.124	−1339.139	32.159**	31.501***	.414	.212
	(98.829)	(56.805)	(2074.673)	(1228.495)	(15.523)	(10.240)	(.518)	(.135)
New MV (not STRV)	61.319	25.450	−511.770	−1937.891	40.725***	30.882***	.272	.158
	(105.933)	(58.249)	(1799.364)	(1176.528)	(12.808)	(9.127)	(.266)	(.109)
STRV	4.723	41.930)	1180.376	−267.888	44.449***	21.477**	.584**	.388**
	(99.138)	(57.113	(1864.116)	(1196.429)	(13.230)	(8.888)	(.273)	(.164)
Hybrid	62.813	15.237	2313.113	69.609	29.024**	24.872**	.264	.337**
	(98.267)	(56.663)	(1610.457)	(1149.113)	(14.157)	(9.651)	(.240)	(.145)
Augmented regression tests								
χ^2 (P value): $\pi_1, \pi_2 = 0$	47.72		11.69		27.44		3.63	
	(.000)		(.166)		(.001)		(.889)	
χ^2 (P value): $\pi_1 = 0$	4.51		3.64		6.26		2.43	
	(.341)		(.457)		(.180)		(.657)	
N obs.	1175		1172		1169		1153	
N households	872		870		868		856	

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively. Standard errors are given in parentheses. All standard errors are robust to heteroskedasticity. The number of observations differs due to missing observations. Full regression results are available in Table A6. The augmented regression tests for $\pi = 0$ test whether the within-household and between-household effects for variety type treatment variables (π_1) and plot-characteristic variables (π_2) are equivalent. In that case, the RE model results are preferred.

TABLE 5 CRE and RE estimates of the effects of variety type on early-season input use from detailed input module.

Variables	Early season chem fertilizer (kg/hectare)		Land prep labor (person-days/hectare)	
	(1)	(2)	(3)	(4)
T_{ij}	CRE	RE	CRE	RE
Variety type				
Old MV	20.437	21.090*	14.382	24.071**
	(18.868)	(10.741)	(20.741)	(11.076)
New MV (not STRV)	21.102*	16.470*	7.936	14.482
	(12.532)	(8.915)	(19.503)	(10.472)
STRV	29.244**	17.105**	29.501*	21.690**
	(11.567)	(8.526)	(17.015)	(10.882)
Hybrid	11.979	14.016	18.439	15.336
	(9.550)	(8.970)	(17.138)	(10.454)
Augmented regression tests				
χ^2 (P value): $\pi_1, \pi_2 = 0$	12.20		18.19	
	(.142)		(.020)	
χ^2 (P value): $\pi_1 = 0$	2.03		1.99	
	(.730)		(.738)	
N obs.	524		525	
N households	392		392	

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively. Standard errors are given in parentheses. All standard errors are robust to heteroskedasticity. The number of observations differs due to missing observations. Full regression results are available in Table A7. The augmented regression tests for $\pi = 0$ test whether the within-household and between-household effects for variety type treatment variables (π_1) and plot-characteristic variables (π_2) are equivalent. In that case, the RE model results are preferred.

TABLE 6 CRE and RE results on the impact of variety type on yield and yield variance.

Variables	Yield (1) CRE	(2) RE without input variables (l = 0)	(3) RE with standard input variables (l = 1)	Yield variance (4) CRE	(5) RE without input variables (l = 0)	(6) RE with standard input variables (l = 1)
T_{ijk}						
Variety type						
Old MV	.295***	.327***	.315***	−.118	−.091	−.095
	(.096)	(.061)	(.061)	(.128)	(.118)	(.114)
New MV (not STRV)	.361***	.426***	.413***	−.184**	−.241***	−.231***
	(.083)	(.055)	(.054)	(.092)	(.072)	(.068)
STRV	.472***	.357***	.350***	−.534**	−.273***	−.269***
	(.104)	(.059)	(.058)	(.212)	(.092)	(.088)
Hybrid	.749***	.721***	.670***	−.304***	−.230***	−.215***
	(.085)	(.060)	(.059)	(.079)	(.082)	(.078)
Augmented regression tests						
χ^2 (P value): $\pi_1, \pi_2, \pi_4 = 0$	15.56			20.84		
	(.113)			(.022)		
χ^2 (P value): $\pi_1 = 0$	7.08			10.93		
	(.217)			(.027)		
N obs.	1488	1488	1488	1488	1488	1488
N plots	1131	1131	1131	1131	1131	1131

Notes: */**/*** denotes statistical significance at 10%/5%/1%, respectively. All standard errors are robust to heteroskedasticity. Full regression results are presented in Table A8.

The augmented regression test for $\pi = 0$ tests whether the within-household and between-household effects for variety type treatment variables ($\pi 1$), plot-characteristic variables (π_2), and seeding characteristics (π_4) are equivalent and thus the RE model results are preferred.

6.2 | Impact of STRV adoption on productivity

We first select the appropriate model and examine yield and yield variance results (β_1 from Equation 3) to provide insights into improved varieties' productivity gains compared to TVs. Next, we compare the RE results with and without endogenous input variables (β_1 from Equation (4), where $l = 0$ and $l = 1$, respectively) to shed light on the source of the productivity gain of improved varieties. We conclude by comparing the effect of adoption on yield outcomes when inputs enter the models with different levels of detail ($l = 1$ and $l = 2$).

The augmented regression test from the yield model suggests that within-plot and between-plot effects of variety type are equivalent ($\pi_1 = 0$) and thus the RE model is preferred (Table 6). For the yield variance model, however, the null hypothesis that $\pi_1 = 0$ is rejected and the CRE model is preferred. According to preferred results, all improved variety types increase yields compared to TVs and all except for old MVs reduce yield variance. STRVs increase yields by 36%, while old MVs, new MVs, and hybrids increase yield by 33%, 43%, and 72%, respectively, compared to TVs (Table 6, column 2). Results from a Wald test confirm that the yield gain of hybrids is statistically higher than those of all other improved variety types, while the yield gain of STRVs is statistically equivalent to that of old MVs and other new MVs (the STRV yield gain is lower than that of other new MVs, but this difference is only significant at a 10% level).

STRVs reduce squared yield residuals by .53 compared to TVs, while hybrids reduce them by .30 and new MVs by .18 (Table 6, column 4). Wald test results reveal that yield variance coefficients for STRVs, new MVs, and hybrids are statistically equivalent (STRV yield variance reduction is greater than that of new MVs but only significant at a 10% significance level). Thus, in a non-stress year, STRVs provide a similar yield and yield variance advantage compared to other new MVs.

Adding input variables into the yield regressions has little effect on model coefficients (Table 6). Yield and yield variance coefficients decline slightly for most variety types when standard input variables are included (Table 6, columns 2 and 3; Table 6, columns 5 and 6). This weakly suggests that accounting for input use attenuates the productivity gain from adoption and that the crowd-in input effect contributes to higher yields and reduced yield variance (Emerick et al., 2016). Adding more detailed input variables compared to the standard input vector has very little effect on estimated coefficients (less than 1%) (Table A9). Thus, including detailed questions on input variables in household surveys may not be important if the main interest is the productivity effects of a new technology.

6.3 | Discussion

Our results indicate that input use is higher for all improved variety types compared to TVs: more chemical fertilizer is applied to all improved types, more pesticides are applied to hybrids and STRVs, more land preparation labor is applied to old MVs and STRVs, and more early-season chemical fertilizer is applied to STRVs. This suggests that all three mechanisms (income, marginal productivity, and downside risk effects) may be important in driving crowd-in effects. While we are not able to isolate these mechanisms, we can assume that the downside risk effect is not the only mechanism influencing farmers because if that were the case, we would expect only STRVs to crowd in input use. However, STRVs have the strongest and most consistent increase in input use across the inputs we examined. In addition, while all improved variety types received more chemical fertilizer, only STRVs received more early-season chemical fertilizer. This evidence suggests that the downside risk effect may be the most influential mechanism. While higher incomes and marginal productivity of inputs likely play a role in farmers' decision-making regarding input use, farmers may be more concerned about the relative risk of experiencing a loss in harvest and thus, their investments into inputs.

In terms of productivity, hybrids are the most beneficial variety, offering the highest yields and a reduction in yield variance similar to STRVs in a non-drought year. Despite this, the evidence for crowd-in effects is weaker for hybrids compared to STRVs. This further suggests that the downside risk effect is more influential than the income effect in driving input use. If the income effect were more influential than the downside risk effect, we would expect hybrids to have the strongest crowd-in effects. This demonstrates how comparing the performance and crowd-in effects of STRVs with those of other improved variety types provides insight into farmer decision making. This insight can help researchers and policymakers weigh different priorities when determining what types of rice varieties to develop and promote.

7 | CONCLUSION

Our study adds to the limited literature finding crowd-in effects of STRV adoption (Emerick et al., 2016; Simtowe et al., 2019). Like Emerick et al. (2016), we find that adoption of STRVs crowds in input use: specifically, early-season chemical fertilizer, total chemical fertilizer, land preparation labor, and pesticides. Other improved varieties also crowd in some inputs, though the STRV crowd-in effects are more consistent. Thus, while increased adoption of all improved variety types will likely play a role in modernizing agriculture via increased input use, adoption of STRVs may have a stronger effect across a wider range of inputs than other variety types. In addition, STRVs increase yield and reduce yield variance compared to TVs in a non-stress year: these effects are comparable to those of other newly released MVs. The yield gain of STRVs is lower than that of hybrids but the reduction in variance is statistically equivalent.

This suggests that even in a non-stress year, there is no yield penalty for STRVs compared to other similar varieties. This is crucial for adoption efforts, as the performance of STRVs in non-drought years is likely a very important factor in farmers' choice of variety. In addition, it is notable that even though hybrids are significantly higher-yielding than STRVs, we found more evidence of crowd-in effects for STRVs compared to hybrids. This evidence suggests that all three mechanisms of crowd-in effects (income, marginal productivity, and downside risk effects) are important.

7.1 | Policy implications

Our results have important implications for policymakers, development organizations, and social science researchers. Most importantly, our results suggest that promoting STRVs may be more impactful in modernizing agricultural practices than the promotion of other improved variety types. Furthermore, there is no yield penalty for growing STRVs compared to other MVs in a non-drought year. Although we found less evidence of crowd-in effects for hybrid varieties compared to STRVs, hybrids performed better in terms of yield, and equally as good in variance reduction as STRVs in a non-drought year. Varietal comparisons may help policymakers, plant breeders, and/or agricultural development organizations choose what types of varieties to develop, promote, or otherwise invest in without neglecting the market segments and their respective targeted product profiles.

The experiment to randomize survey design offers insights for researchers and practitioners. Collecting more granular input data allows for a more nuanced exploration of the crowd-in effects of STRV adoption; without this data, we would not have identified the impacts of STRVs on early-season fertilizer use or land preparation labor. Therefore, for researchers evaluating the crowd-in effects of agricultural technologies, detailed data may strengthen their evaluation. Collecting basic input information may be preferred for studies focusing on the productivity effects of technology adoption.

7.2 | Limitations and future research

There are some limitations to our study. Many households cultivate only one rice plot and many rice plots have only one variety, and our methodology is unable to use information from these observations. For the analysis of input crowd-in effects, we are unable to control for unobserved plot-level heterogeneity, which could potentially bias our results. Nevertheless, by controlling for household-level heterogeneity and including several plot characteristics in our regressions, we feel confident in our results. The results are also consistent with recent research that finds that STRVs crowd in inputs (Emerick et al., 2016; Simtowe et al., 2019). Finally, we are only able to analyze varietal performance in a non-drought year, which makes us unable to evaluate the effects of STRV adoption when they would likely have the strongest impacts.

Further research is needed to more fully understand the impacts of STRVs on farmer decision-making and outcomes in years with and without climate stresses. Research conducted in different settings and with different methods of analysis will provide the greatest insights; for instance, crowd-in effects may be stronger in areas that have recently experienced drought. It may be particularly important to see how hybrids perform in a drought year for policymakers, farmers, and agricultural specialists to understand how they compare with STRVs across different climatic conditions. This will help to ensure that investments made into seed development and delivery will enable farmers to be productive, efficient, and resilient in the face of a changing climate.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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