The System of Rice Intensification and Its Impacts on Household Income and Child Schooling: Evidence from Rural Indonesia

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Abstract:

The yield potential of a set of improved rice management practices, known as the System of Rice Intensification (SRI), has attracted much attention. Yet, we know surprisingly little about SRI's impact on socio-economic outcomes, although the casual assumption abounds that higher yields imply higher income and other welfare improvements for farmers who practice SRI. Using original data from Indonesia, this study assesses the impact of SRI on farm and off-farm incomes as well as on the use of family labor time and child schooling. The matching estimator shows that SRI generates estimated yield gains of 64%. However, due presumably to a significant increase in the use of family labor on farm, SRI users earn significantly lower off-farm incomes such that users enjoy no net household income gains from SRI. Despite the increased labor demand for farming, we find no evidence of a child labor effect of SRI.

JEL Classification: D1, O13, O33, Q12

Keywords: Agricultural Technology, Impact Evaluation, Matching, Rural Development, Indonesia

Introduction

The adoption of improved agricultural technologies is crucial to the process of economic development and rural income growth (David and Otsuka, 1994; Otsuka, Estudillo, and Sawada, 2009, Barrett, Carter and Timmer, 2010). The Green Revolution package of fertilizers, irrigation and high-yielding improved seeds was a typical example of “science-based” innovation, where innovations were repeatedly tested and scientifically validated before introduction to farmers, leading to significant productivity and income gains among adopters of the new technologies (David and Otsuka, 1994; Hayami and Godo, 2005). By contrast, a novel recent approach to rice cultivation, the System of Rice Intensification (SRI), has attracted considerable attention despite its origination outside the conventional plant breeding system and its rapid spread among farmers “without the clear stamp of scientific approval” (Glover, 2011). In part because of its nontraditional development and diffusion path, SRI has proved extremely controversial. As disputes have raged about SRI’s agronomic performance and potential, the net effects on the economic welfare of SRI adopting households have attracted surprisingly little study.

The primary objective of this study is, therefore, to examine the household-level socio-economic effects of SRI use. SRI has been often pitched as a pro-poor technology in that it can reduce farmer expenditure on external inputs such as seed, water and fertilizer (Berkhout and Glover, 2011). But no solid evidence has thus far emerged demonstrating how SRI use affects total household income or other indicators of household well-being, such as children's school attendance. Existing observational and experimental studies concentrate only on the impact of SRI use on rice yield or, at best, on rice income. Since farmers generally diversify their income sources among a range of on-farm and off-farm activities, and income growth in one activity might come from reallocation of labor, land or other resources from other activities, we cannot reliably infer the welfare consequences of SRI from such results. This is particularly relevant because some studies find that SRI requires intensive labor inputs for land preparation, crop care as well as water management, especially at the early phase of adoption (Moser and Barrett, 2003, 2006; Barrett et al., 2004; Berkhout and Glover, 2011). If the increased SRI rice yields are achieved (at least partly) by reallocating labor from other economic activities, net income gains could be attenuated or negligible even with the increased rice productivity and income. To the best of our knowledge, only Noltze, Schwarze and Qaim (2013) have explored the household income impacts of SRI. Like us, they find strong yield but negligible income effects of SRI in Timor Leste. But they do not unpack the labor reallocation effects across income-generating activities we study nor do they explore child schooling impacts. This study aims to fill important knowledge gaps about SRI by addressing these issues.

We use primary data collected in Indonesia, where rice is the staple crop for the vast majority of population and its productivity growth has long been a significant political concern

(McCulloch and Timmer, 2008). By examining impacts of SRI not only on rice yield, but also on total household income and children's school enrollment, this paper significantly extends the existing knowledge of the impacts of SRI use. Our estimated results suggest that SRI generates substantial average yield gains of around 64%, controlling for household and plot heterogeneity that correlates with SRI use. However, due presumably to the increased use of family labor on farm, we found significant evidence that SRI users earn lower off-farm incomes. As the increased farm income is largely offset by decreased off-farm income, there is no statistically significant difference in total household income between SRI users and non-users. In spite of the increased labor demand for farming, however, Indonesian farm households do not appear to withdraw children from school; we find no evidence of a child labor effect of SRI use.

SRI

The System of Rice Intensification (SRI), pioneered by a French missionary priest in rural Madagascar in the mid-1980s, is characterized by changing a range of rice management practices, consisting of : (1) early transplanting of seedlings, 8-12 days old, (2) shallow planting (1–2 cm) of one or two seedlings, (3) sparse planting in checkrows (more than 20 × 20 cm), and (4) intermittent irrigation (Noltze, Schwarze and Qaim, 2012).[1] Neither new seed variety nor additional external inputs is required (Barrett et al. 2004; Thakur, 2010; Glover 2011). It is, however, generally held that SRI is more complex and more intensively uses labor. For example, SRI requires more intensive field preparation, especially leveling to facilitate proper water control, as well as frequent (typically daily) visits to fields to check the water level (Rakotomalala, 1997; Barrett et al., 2004). Also, regular and frequent weeding is crucial, especially in the early transplanting stage, because weeds compete with tiny young seedling in the field (Berkhout and Glover, 2011). Furthermore, increased labor demand for transplanting is often reported for carefully spaced and arranged transplanting. According to Rakotomalala (1997), 62% of the extra labor for SRI is needed for weeding and 17% for transplanting.

While SRI practices tend to require more careful management, it reportedly achieves greater yields than conventional management practices due to synergistic effects among these practices and on-farm trials have consistently shown remarkable yield increments in various countries (Uphoff et al. 2002; Sato and Uphoff, 2007; Sinha and Talati, 2007; Stoop, Uphoff, and Kassam, 2002; Thakur et al., 2010; Berkhout and Glover, 2011).

Yet these claims have been challenged by crop scientists as they have not been fully validated by conventional agronomic methods. For example, Sheehy el al. (2004) scoff that reported SRI yields of more than 20 tons per hectare would exceed the theoretical prediction of maximum output, and they would result from measurement errors. They also find no significant yield differences between SRI and conventional management practices under well-controlled experimental conditions in China. McDonald, Hobbs, and Riha (2006) review 40 published journal articles, mostly from experimental fields, and conclude that outside of Madagascar, where soil conditions are especially suitable to SRI practices, SRI has negligible or even negative impacts on rice yield. Yet, these critiques are also contested and the apparent benefits of increased yields under SRI are widely documented from a range of sites (Thakur, 2010).

It is not uncommon to observe differences between on-farm and on-station results, although the differences commonly run the opposite direction, with lower yields on farmers' fields than in researcher-managed trials on experiment station plots (Glover, 2011). It may be the case that SRI is only partially or wrongly implemented in experimental fields (Uphoff, Kassam, and Stoop, 2008). On the other hand, it is also possible that observed on-farm results are overstated by favorable farmer and plot characteristics underlying SRI use, i.e., by selection on observables or unobservables. Indeed, using data on SRI and non-SRI plots among partial adopters in Madagascar, Barrett et al. (2004) find that household- and farmer-specific effects and plot characteristics account for more than half of observed yield gains on SRI fields, although even the conditional gains were substantial, averaging 84%. Such heterogeneity and self-selection of technological adoption can lead to spurious relationships between technological change and resultant outcomes (Mendola, 2007). In order to establish the causal effect of technology choice, therefore, it is critical to take the selection process into consideration, as well as the mechanisms that might lead to selection on observables, unobservables or both. Hence our empirical strategy for identifying SRI's impacts on various indicators of productivity and household well-being.

Empirical Strategies

The major objective of this study is to explore the impacts of SRI use, measured by the average treatment effect on the treated (ATT). ATT computes the average difference in outcomes of SRI users with and without a technology:

$$ATT = E(y_{1i} - y_{0i} \mid D_i = 1) = E(y_{1i} \mid D_i = 1) - E(y_{0i} \mid D_i = 1), \qquad (1)$$

where $E(\cdot)$ denotes an expectation operator, y_{1i} is an outcome of interest of household (or plot; hereafter we use "household" as representation of subscript) i with SRI, y_{0i} is the outcome of the same household without SRI, and D is a treatment indicator equal to 1 if the household actually uses SRI and 0 otherwise. The fundamental problem in estimating equation (1) is that it is impossible to observe the outcome of SRI users had they not used, i.e., $(y_{0i} \mid D_i = 1)$. Thus, with observational data, one may be inclined to simply compare outcomes between SRI users and non-users. Yet, as is well known, such an analysis will likely result in biased estimates, expressed by

$$[E(y_{1i} \mid D_i = 1) - E(y_{0i} \mid D_i = 0)] = ATT + [E(y_{0i} \mid D_i = 1) - E(y_{0i} \mid D_i = 0)]. \quad (2)$$

The left-hand side of equation (2) measures the average difference in outcome between actual SRI users and non-users, while the last term of the right-hand side indicates the magnitude of bias from the true ATT due to differential outcomes between SRI users and non-users in the absence of SRI.

We use propensity score matching (PSM), introduced by Rosenbaum and Rubin (1983), with added controls to try to eliminate the bias due to the bracketed term on the right-hand side of equation (2). PSM relies on an assumption of conditional independence, where conditional on the probability of SRI use given observable covariates, an outcome of interest in the absence of treatment, y_{0i}, and SRI use, D_i, are statistically independent. This leads to:

$$E(y_{0i} \mid D_i = 1, p(x_i)) = E(y_{0i} \mid D_i = 0, p(x_i)),$$

where $p(x_i)$ denotes the probability of SRI use given characteristics x, which is defined as:

$$\Pr(D_i = 1 \mid x_i) \equiv p(x_i).$$

PSM thereby eliminates bias that might otherwise result from selection on observed characteristics.

Another important assumption of PSM is the common support condition,which requires substantial overlap in covariates between SRI users and non-users, so that households being compared have a common probability of both being user and non-user, such that 0< $p(x_i) < 1$.

If these two assumptions are fulfilled, then the PSM estimator for ATT can be specified as the mean difference of the SRI users matched with non-users who are balanced on the propensity scores and lie within the region of common support, expressed as:

$$ATT^{PSM} = E[y_{1i} \mid D_i = 1, p(x_i)] - E[y_{0i} \mid D_i = 0, p(x_i)].$$

The above PSM estimator yields consistent estimates of the ATT if covariates x properly characterize the use of SRI. Selection of x is therefore an important issue.[2] It is recommended that all factors affecting adoption decisions and outcomes are included (Heckman, Ichimura, and Todd, 1997; Caliendo and Kopeinig, 2008).

A key limitation of the PSM method is that if unobservable factors affect adoption decisions, estimated ATT may be biased by selection on those unobservables (Smith and Todd, 2003). Yet, the literature suggests that unobservable factors, such as farmers' skill, risk preferences, and networking ability, may play an important role in technology adoption (Feder, Just, and Zilberman, 1985; Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Miyata and Sawada, 2006; Munshi, 2004; Conley and Udry, 2010). We try to minimize selection-on-unobservables bias by controlling for variables that are generally unobservable or not readily gathered in conventional surveys. Specifically, we conduct a simple experimental exercise to elicit estimated risk preferences, following Binswanger (1980) and Holt and Laury (2002). In addition, we construct proxy variables capturing social learning opportunities, following Bandiera and Rasul (2006).[3] By explicitly incorporating these factors in x we reduce the likelihood and magnitude of bias based on selection on unobservables (Barrett and Carter, 2010).

It is virtually impossible, however, to control for all relevant unobservables. We therefore test whether unobservables might affect our estimated results using the sensitivity tests proposed by Rosenbaum (2002) and Ichino, Mealli and Nannicini (2008). Because a management-intensive technique subject to considerable intrinsic heterogeneity, like SRI, does not lend itself to a randomized controlled trial (Barrett and Carter, 2010), the approach we take is likely as close as one can feasibly come to statistical identification of the causal effects of SRI use on household outcomes such as income and children's school enrollment.

Data

The data were collected in a survey fielded in Kelara Karalloe (KK) in Jeneponto District, South Sulawesi Province, Indonesia. KK is on the south coast of South Sulawesi, with about 105 km to the south of the provincial capital, Makassar. Jeneponto is one of Indonesia's poorest districts. While agriculture is the dominant income source for most rural households, annual average rainfall is less than 1,500 mm, which prevents farmers from cultivating crops in the dry season in the absence of sufficient irrigation. Moreover, KK is located in hilly areas and most rice fields are terraced. Thus, plots are quite small, around 0.4 ha on average. Given water scarcity and limited land availability, it is not uncommon that farmers in KK migrate to Makassar to seek employment opportunities in the dry season.

In an attempt to alleviate poverty and raise farmers' living standards, an irrigation rehabilitation scheme was implemented in KK from 1998 to 2003, and SRI was introduced and promoted beginning in 2002. Irrigation covers 7199 hectares for 51 Water Users Associations (WUA) under 4 Water Users Association Federations (WUAF) within the scheme.

In 2009, the lead author collected data on rice growing households in KK. To select the sample households, upstream, midstream, and downstream WUAs were first identified using the irrigation rehabilitation plan provided by the project consultant. We then randomly selected 24 WUAs based on the probability proportional to the population share and 30 households from each sampled WUA using the comprehensive list of WUA members. Additionally, six non-irrigated sub-villages neighboring selected WUAs and 30 households from each selected sub-village were randomly chosen for the sample.

The survey collected detailed information on household socio-economic conditions, household and plot characteristics, experience with SRI, on-farm and off-farm income earning activities as well as wage earnings separately by season. The present study focuses only on wet season data because about 40% of sample plots were left fallow in the dry season, making it difficult to meaningfully compare outcomes in the dry season, such as yield between SRI users and non-users. Among 900 sample households, 36 households were dropped either because they do not cultivate rice during the observation period or because they have important missing values. Hence, the total sample size became 864 farmers operating 1202 rice plots.

Household and Plot Characteristics

Table 1 presents selected descriptive statistics derived from the wet season data. The average age of household heads is about 50 years and they are mostly male with just over six years of education.[4] The average household size is 5.2, and the male-female ratio is close to one. As described previously, most rice fields are terraced and each plot is small. On average, sample households cultivate 1.4 plots in the wet season and the sum of cultivated rice fields is only around 0.6 hectare. At the plot level, about 80% of plots are irrigated. Owner-cultivators predominate, followed by share-tenants (called *Tesan*) who typically equally divide net income with the landowner.[5]

We classify a household as an SRI user if it employs at least one core component of SRI on any rice field in the 2009 wet season, and a plot as in SRI if it employs at least one core component of SRI in the 2009 wet season, with the four core components being: (1) early transplanting of seedlings, 8-12 days old, (2) shallow planting (1–2 cm) of one or two seedlings,

(3) sparse planting in checkrows (more than 20 × 20 cm), and (4) intermittent irrigation. By this metric, 14.1% of sample households and 14.0% of sample plots apply SRI. The average years of SRI experience are 0.7 unconditionally and 4.3 conditional on currently using SRI. The adoption rate of each component at the time of survey varies slightly at the plot level. Almost all SRI plots apply early transplanting, shallow planting, and sparse planting, while the adoption rate of intermittent irrigation, conditional on SRI use, is relatively low at 79.8%. Only 71.4% of plots adopt all four components of SRI. Because the combination of practices appears related to SRI's impacts, we check our results for robustness to alternative definitions of SRI in terms of uptake of combinations of these four core components.

Outcome Indicators by SRI status

Table 2 reports unconditional differences in variables of interest by SRI use status. Among plot level outcomes, we are particularly interested in land and labor productivity of rice production, while as household level, we focus on farm and off-farm incomes. Off-farm income is further decomposed into non-farm self-employed income and off-farm wage earnings, including both non-agricultural and agricultural wage earnings in the wet season. On-farm income and self-employed non-farm income are computed by deducting all enterprise cash expenditures from gross revenues in the same reference period.[6] We emphasize that we are therefore studying quasi-profits not true economic profit since these estimates do not account for unpaid use of household labor and owned land and equipment. Since our focus is on the impact of SRI use on labor earnings through changing the allocation of family labor, the total household labor income we report does not include unearned income, such as remittances.[7]

The average yield of SRI plot is about 5.5 ton/ha (T/HA), which statistically significantly exceeds yields on non-SRI plots, which are only 3.0 T/HA (Table 2). Similarly, labor productivity is statistically significantly higher for SRI plots, with 132kg per family labor-day,[8] compared to non-SRI plots, which are only 76kg per family labor-day. Also, rice income per hectare as well as rice income per family labor-day is substantially greater on SRI plots, and the differences are statistically significant at the 1% level.[9] This pattern holds at the household level as well; monthly on-farm income of SRI users (Rp732,500) is more than threefold that of non-users (Rp238,800).

Note that SRI users also generate higher off-farm incomes than non-users, although the difference is not statistically significant (Table 2). In total, because of significantly greater on-farm income and modestly (but statistically insignificantly) higher off-farm incomes, SRI users are significantly better off than non-users. On average, SRI users earn more than 70% higher income than non-users. It is unclear in the descriptive statistics, however, whether this reflects favorable income impacts of SRI use or ex ante attributes of SRI farmers that make them better off than non-users irrespective of SRI use.

We are interested not only in short-term, household income metrics of welfare but also in children's enrollment in school as an indicator of longer-term well-being and household (non-farm) investment behavior.[10] If SRI boosts farm labor productivity and demands, as seems the case from prior studies, then the opportunity cost of schooling increases and could induce a reallocation of children's time from schooling to farm tasks such as field leveling, weeding, transplanting, water management or harvesting. But it is also true that child labor supply responsiveness typically falls with household income, because (foregone) child earnings represent a smaller share of household resources, because of greater capacity to engage (hired or mechanical) substitutes for child labor, and because the marginal propensity to invest in education increases with income (Basu, 1999). Thus income and substitution effects exist and it is unclear which dominates, if either, and thus worth investigation empirically.

Learning and Risk Preferences

Given its remarkable productivity and earnings benefits, low uptake of SRI seems rather puzzling. One mooted cause of such low uptake is that SRI requires more labor inputs. While the use of hired labor is common, it is usually limited to simple tasks, such as transplanting and harvesting, for which hired workers are paid piece rate wages. Core activities that require greater care and judgment are implemented exclusively by family labor. Detailed analysis of our data confirms that family labor inputs per hectare are statistically significantly larger for SRI plots than non-SRI plots: 64 versus 54 person days. Barrett et al. (2004) find that SRI's labor requirements fall with years of SRI experience. In our data, however, there is no discernible change in family labor input per hectare on SRI plots out to nine years of SRI experience.

Another possible factor explaining low SRI uptake is the lack of learning opportunities. In the study area, SRI was introduced and promoted by Japanese consultants, but after the termination of aid projects, no continuous extension services were implemented. Farmers frequently mention the importance of learning the method since SRI is a knowledge-intensive cultivation technique. Without available extension services, farmers who want to learn about SRI may look for neighbors who have either information about or, especially personal experience with it (Miyata and Sawada, 2006; Maertens and Barrett, 2012). To capture such social learning opportunities, we asked farmers to list the agricultural advisors in their social network. Agricultural advisors are defined as "significant others" whom farmers consult for farming practices and with whom they frequently exchange information about each other's experience. These include WUA leaders, land owners, farmer group leaders, village informal leaders, and neighbors. Farmers were asked to select up to five advisors of whom they frequently ask advice, and then asked whether those five advisors ever used SRI. Sample farmers have, on average, 0.8

advisors and only 17% of them have advisors who have ever used SRI. Farmers who use SRI tend to consult with others with prior SRI experience relative to those who do not use SRI.

Risk aversion may be another factor that explains low uptake of SRI, as SRI has been found to exhibit higher yield variance than traditional rice cultivation (Barrett et al., 2004). In order to examine risk preferences, we conducted a common experimental exercise in the field, reflected by the hypothetical payoff matrix in Table 3.[11] The respondents were adult household members and overwhelmingly the household head who makes most rice technology adoption decisions, ensuring that the elicited preference parameter is relevant for the purpose of our analysis. Option A always offers Rp50,000 with probability one, while Option B offers a higher payoff of Rp75,000 with probability 0.5 and a lower payoff of a certain amount with a probability of 0.5; the lower payoff becomes smaller as the exercise progresses. In Exercise 1, Option B should always be preferred because the lower payoff equals the sure payoff of Option A, with a positive probability of getting more. We offered this option merely to help respondents understand how this exercise works. Then, we ask a series of lottery choices from top to bottom and determined when respondents switch from Option B to Option A.[12] Since the expected payoffs of Option A and Option B become indifferent at the Exercise 4, a risk-neutral person will switch preference when or just after facing this option. On the other hand, a risk-loving person should continue to choose Option B even after the Exercise 5, in search of higher returns. In this way, we can classify respondents' risk tolerance into risk-averse, risk-neutral, and risk-loving categories, depending on the point at which respondents switch options.

The experimental elicitation of risk preferences worked relatively well. Figure 1 demonstrates the cumulative proportion of respondents who switch to Option A (safer choice) in each exercise, separately by SRI adoption status.[13] All respondents selected Option B in Exercise 1, as theory would predict. But most respondents switch to option A even at Exercise 2, where the lower payoff in Option B is reduced only by Rp5,000 from the Exercise 1. This clearly indicates that most sample respondents are risk averse. In fact, roughly 85% of respondents exhibit risk aversion (i.e., those switch to Option A before Exercise 4), with no significant distinction based on SRI adoption status. The cumulative proportion of respondents who remain in Option B is slightly larger for households using SRI than among non-users, as one would expect, implying that SRI users are slightly less risk averse than non-users. But the differences are too small to explain uptake patterns, although they remain an important control for unobservable characteristics that may affect uptake and household well-being.

Propensity Score Estimation of SRI Use

As a first step, we estimate the plot-level SRI use by probit, with the binary dependent variable equal to one if the plot uses SRI and zero otherwise. In addition to relevant observable characteristics, such as water availability, land endowment, and household demographic characteristics, we include social learning opportunities, represented by the number of agricultural technology advisors and the dummy equal to 1 if at least one of them ever uses SRI, as well as dummies for ordinal risk preferences, with risk neutral households as a reference category.[14] The estimation results with robust standard errors are presented in Table 4.[15] The pseudo-r^2 is about 0.38, which indicates a reasonably good fit of the model.

Note that the objective of this first stage propensity score estimation is to balance the important observable covariates underlying SRI use between SRI plots and non-SRI plots, not to establish causal relationships between covariates and SRI use. Our objective is to estimate the impacts of farmers' choice to employ SRI or not in the 2009 wet season we study, not to make causal inferences about patterns of SRI practice among farmers. We therefore caution against causal interpretation of the results presented in Table 4. Given that SRI was first introduced into the area in 2002 and our data were collected in 2009, we cannot control for pre-SRI conditions and thus some of the righthand side variables may have evolved in response to the introduction of SRI. Or more subtle forms of endogeneity may likewise affect some covariates. For example, our social learning variables may be endogenous and would suffer from reflection problems discussed by Manski (1993). However, omitting variables that are strongly correlated with SRI use can bias estimation results on the average treatment effects, which is a more serious consequence for our purpose. Since the social learning variables are highly significantly correlated with SRI use, as will be discussed below, we maintain these variables.[16] But note that any endogenous component of these regressors generates correlation between covariates and the error term akin to the selection-on-unobservables problem. Thus tests for the robustness of results in the face of prospective selection-on-unobservables provide an effective check on the qualitative impact findings even if some of the first-stage regressors are endogenous.

Although detailed inference about the causal mechanisms of SRI use is not appropriate given the potential endogeneity concerns around some of the probit regressors, most of the variables included have the expected signs, signaling that the associations we expect indeed hold. Water availability, captured by dummies for upstream and midstream as well as the dummy for the plot near the irrigation canal, are positive and significantly associated with SRI use, indicating that SRI tends to be applied when supply of irrigation water is more reliable and timely water management for altenate wetting and drying is much easier. The number of plots a household operates is negatively correlated with SRI use, presumably because the increased number of plots reduces the ability to closely manage each plot as this method requires greater cropping care and timely water management. The size of each plot is positively correlated with SRI use, implying that farmers appear more likely to experiment with a new method on larger plots, as found in previous studies (Barrett et al., 2004; Berkhout and Glover, 2011; Noltze, Schwaltz, and Qaim, 2012,2013).

Moving to household demographic characteristics, female-headed households are less likely to apply SRI. Completed years of household head education do not influence SRI use. The number of working-age (15 years old and above) household members is positively associated with SRI use, consistent with our expectation that the household labor endowment affects uptake because of SRI's increased demand for labor.

The number of agricultural technology advisors is not associated with the SRI use, while having at least one advisor with SRI experience statistically significantly increases the probability of practicing SRI at the 1% level, implying that the use of SRI is correlated within social networks.[17] As expected, risk averse farmers are less likely to apply SRI, presumably because of the increased production risks associated with SRI use.

Overall, our results are consistent with prior studies of SRI adoption. The most important covariates correlated with SRI use include water availability, family labor endowment, learning opportunities, and risk preferences.

Using the parameters obtained by the probit estimation, we compute propensity scores (i.e., the probability of SRI use) for all plots. In order to estimate SRI's impacts over observations of SRI plots and non-SRI plots having common support, we drop the observations of SRI plots with propensity scores higher than the maximum or lower than the minimum of those not in SRI. It is well known that there are different matching algorithms, each with positive and negative attributes (Caliendo and Kopeinig, 2008). Among available options, the nearest neighbor matching and kernel matching methods are most commonly used. The former employs as the counterfactual of the treatment group (SRI plots) those members of the control group (non-SRI plots) that are closest in terms of propensity scores. Yet, as Figure 2 suggests, the distribution of the propensity score of non-users in our sample is highly skewed to the right, while that of users is skewed oppositely. This raises a concern about matching relatively dissimilar plots under the nearest neighbor matching method. We therefore report exclusively the results based on kernel matching, which uses the weighted averages of all non-SRI plots to estimate counterfactual outcomes, where the weight is inversely proportional to the propensity score distance between SRI plots and non-SRI plots. We did, however, also confirm that our results are qualitatively unchanged when using alternative matching estimators, such as nearest neighbor.[18] We ultimately drop 12 treated observations that do not meet the common support condition. To estimate the ATT, we employ an Epanechnikov kernel with a bandwidth of 0.06, obtaining standard errors by bootstrapping with 100 replications.

We performed a series of balancing tests on the differences in means to investigate whether the kernel matched non-SRI plots have characteristics similar to the matched SRI plots.

As the results in Appendix 1 show, although many characteristics statistically significantly differ between SRI and non-SRI plots before matching, no variables are statistically different at the 10% level after matching. Thus the matching procedure is successful in generating relevant comparison groups to infer the causal impact of SRI controlling for observable household and plot characteristics.

The Estimated Impacts of SRI Use

Having obtained matched observations, we discuss the results of the average treatment effects on the treated (ATT) of SRI use.

Rice Production and Income

The outcomes of initial interest are land and labor productivity of paddy production and rice income, as well as family labor inputs at the plot level. As shown in Table 5, paddy yield on SRI plots is about 5.5 T/HA, which is 2.2 T/HA (64%) greater than that of non-SRI plots.[19] The gap is statistically significant at the 1% level, reinforcing the growing evidence of considerable rice yield gains associated with SRI use. Similarly, rice income per hectare is greater on SRI plots, by about Rp 3.5 million (107%), also statistically significant at the 1% level, implying that the SRI method allows farmers to generate more than twice the rice income per unit cultivated area than they get under conventional practices, controlling for the observable heterogeneity of household and plot characteristics. Farmer cash expenses increase an estimated 25% under SRI use, from Rp2.94 to 3.68 million/hectare (estimates not shown), contrary to proponents' promotion of SRI as a low external input agricultural practice. But the quasi-profit gains exceed the yield gains because gross revenues grow slightly faster than cash costs, and rice quasi-profit is already significantly positive under traditional cultivation practices, about Rp 3.27 million per hectare.[20]

It might be argued, however, that SRI's apparent economic profitability might be less if we take into account unpaid family labor costs, especially if SRI requires more intensive labor inputs. This conjecture is partly supported in Table 5, which shows person days of family labor input by plot SRI status. After matches, family labor input per hectare is 16.0 person days (34%) higher on SRI plots. This is consistent with the literature that shows significant increases in labor inputs for SRI plots (Rakotomalala, 1997; Barrett et al., 2004). Given the prevailing unskilled agricultural wage rate of Rp20,000/day, SRI users forego average off-farm unskilled earnings of only Rp320,000 per hectare seasonally, equivalent to only about ten percent of the income gains per hectare brought about by SRI. So SRI indeed seems profitable among these Indonesian farmers.

The profitability gains come almost entirely from increased land productivity, as Ly et al. (2012) likewise find. The estimated increased rice output of 25.2% (26.5 kg/personday) is statistically significant only at the 10% level and the magnitude is relatively small, although net rice income per person day jumps by 77.4%, a statistically and economically significant amount. As we show below, however, the apparent partial profitability gains to labor do not stand up to robustness checks, while the land productivity gains do, reinforcing the impression from Table 5 that the gains accrue mainly to land, not labor.

The main results on land productivity appear insensitive to unobserved characteristics. We present the Rosenbaum bounds test critical values in the final column of Table 5 in those cases where the estimated ATT is statistically significantly different from zero. For example, the lowest critical value producing a 95% confidence interval encompassing zero is 3.6 for rice yield. This means that the unobserved characteristics would have to increase the odds ratio of SRI use by 260% before it would alter inference with respect to the superior yield performance of SRI. Although there is no clear-cut critical threshold that distinguishes the existence and non-existence of hidden bias, the larger the critical value, the less sensitive are findings based on observables to hidden bias (Rosenbaum, 2002). Based on the estimated critical values, we consider our results on land productivity relatively less sensitive to bias based on selection-on-unobservables, while those on increased labor inputs and labor productivity should be interpreted with greater caution as those findings may be sensitive to the omission of relevant unobserved characteristics of households and/or plots.[21]

Off-farm and Total Labor Income

Because SRI seems to increase rice productivity, as reflected not just in higher rice yields but also in the apparent reallocation of unpaid family labor to SRI plots, the increased labor use on farm in turn might lead to the reduction of time spent on other meaningful activities, including adult time spent in non-farm activities and children's time spent in school. In order to identify the broader, household-level impacts of SRI, this subsection estimates the impacts of SRI use on off-farm incomes at the household level. The next subsection reports on SRI's estimated impacts on children's school enrollment.

Because off-farm incomes are observed at the household level, we re-estimated the probit regression of SRI use at the household (rather than plot) level to obtain relevant treatment and comparison groups, using the same definition of SRI use (applying at least one of the four components) and explanatory variables as before.[22] The qualitative inference on the estimation of the household-level SRI use probit is substantially similar to the plot-level estimation, as shown in Appendix 2. We then use those estimation results to generate the propensity scores following the same method, using kernel matching for observations on common support, where seven treated observations outside of the common support are dropped.[23]

Table 6 reports the estimated ATT of SRI use on monthly farm and off-farm incomes as well as those on household total labor incomes, i.e., sum of on- and off-farm incomes (but omitting remittances and other unearned income sources), estimated by the kernel matching method. Consistent with the previous subsection, household farm income is significantly higher among SRI users than among non-users, by more than 150%. Nonetheless, it is also clear that the application of SRI is negatively associated with off-farm income in SRI using households. While non-users earn Rp976,820/month off-farm, on average, households practicing SRI earn only Rp571,620, a 78% difference that is statistically significant at the 5% level. By component, off-farm wage earnings, consisting of agricultural and non-agricultural wage earnings, are statistically indistinguishable between SRI users and non-users, while self-employed non-farm income is statistically significantly greater among non-users. Breaking down income generation by the gender of the income earner, we find that SRI use is associated with statistically significantly lower off-farm income by women. This likely reflects SRI's greater labor needs for transplanting, weeding, water management, harvesting and threshing, all tasks largely supported by females in this setting.

These results together suggest that although SRI substantially increases rice income, these gains reflect in part induced labor reallocation from off-farm activities, especially by women. As a result, total monthly household labor income is not statistically significantly different for SRI users than non-users; the point estimate of the difference is less than one percent. These estimated results are largely insensitive to hidden bias with the critical values close to or higher than two.

Possible Side Effects On Child Schooling

Given the increased labor demand associated with SRI and the apparent reallocation of women's time from off-farm income earning opportunities to SRI cultivation, one might reasonably worry that SRI cultivating households likewise increase child labor. In the extreme, this might induce parents to withdraw children from school given the increased value of their labor time. A less extreme impact might be that increased child work on farm leads to occasional school absence and reduced time spent studying away from school, resulting in delayed educational progress, manifest in children falling behind relative to age-appropriate year of school.[24] [25]

We check for such effects by generating ATT estimates of child schooling between SRI users and non-users. We constructed two household indicators: the proportion of school-aged children (6-14 years old) [26] attending school at the time of survey and the proportion of school-aged children whose education lags behind normal progress, where children typically enter primary school at six years of age and progress one grade per year. We further separate each schooling indicator by the gender of children in the household to check whether the gendered impacts on off-farm earnings are replicated in child labor effects on schooling.

We find no evidence of any side effect of SRI's labor demands on child school enrollment (Table 7). The proportion of school-aged children who actually go to school is statistically indistinguishable between SRI users and non-users, regardless of gender of children. Similarly, the proportion of children suffering schooling delays is very similar between them. In economic terms, the income effects of increased productivity offset whatever substitution effects might be generated by the increasing opportunity cost of child time due to enhanced rice labor productivity under SRI. We cannot establish whether any compensatory reduction takes place in the time children spend in leisure or other pursuits but it does not appear that the induced labor demand effects of SRI have any impact on child schooling in this setting, as one might reasonably fear.

Robustness Checks

As a key robustness check, we explore whether the definition of SRI employed in this study matters. Uphoff, Kassam and Stoop (2008) criticizes McDonald, Hobbs, and Riha (2006)'s main finding – which shows SRI has negligible impacts on yield in most countries - because most studies covered in McDonald, Hobbs, and Riha (2006) apply only a few core components of SRI. Uphoff, Kassam and Stoop (2008) argued that the estimated results will differ if every study applies all components of SRI. Bouman (2012) and Palanasami (2010) also point out that defining partial or full adoption as "SRI" may potentially alter the conclusion of the research.

As a robustness check to address this valid concern, we redo all the analysis under the stricter definition of SRI users as only those plots or households that apply all four core components of SRI. In order to compare full-users with non-users, partial users' observations are dropped from the analysis. Table 8 demonstrates that changing to a stricter definition of SRI use does not affect our main findings. Again, rice yield, rice income, and labor inputs per hectare are all significantly greater for SRI plots. With this stricter definition of SRI, the increased returns to labor from SRI use become statistically insignificantly different from zero, reinforcing our earlier point that the partial factor productivity gains of SRI appear to accrue mainly to land, not labor. In addition, due to the increased labor inputs on farm, off-farm labor income of SRI users, especially from self-employed sources, is significantly lower than that of non-users. As a result, there is no statistical difference in total household labor income between SRI users and non-users. Thus, our qualitative results appear robust regardless of the definition of SRI.

Conclusions

In Indonesia, as in many other countries in which rice is a staple food crop, growth in rice productivity has long been among the most important agricultural policy objectives (McCulloch and Timmer, 2008). In direct response to that policy objective, and based on considerable recent publicity that SRI has received as a potential source of considerable productivity gains, the system was recently introduced in Indonesia. But the broader economic impacts of SRI remain largely unstudied. This study explores the various impacts of SRI on rice yields, labor use and productivity on rice plots, households' rice, whole farm and off-farm incomes, and children's school attendance using original data collected in rural Indonesia.

We first investigated the factors associated with SRI use by incorporating generally-unobservable characteristics such as risk preference and social networks into probit estimation of the first stage in propensity score matching. We found that the probability of SRI use increases with better water and labor availability and social networks' experience with SRI, and decreases with risk aversion. Controlling for heterogeneity in plot- and household-level observables, we found that yield and rice income per hectare on SRI plots are statistically significantly higher than non-SRI plots and by a considerable margin, 64% and 107%, respectively. SRI indeed appears more productive a rice cultivation method in these data.

The story is, however, somewhat more complicated because SRI also induces increased use of unpaid family labor and there are little or no gains to average rice labor productivity under SRI. The result is that increased farm income is partly achieved at the cost of the decreased off-farm income, induced by reallocation of labor from off-farm activities, especially women's self-employment, to farm activities. With these countervailing effects, there is statistically no difference in total household labor income between SRI and non-SRI households. The apparent increase in farm labor demand nonetheless does not seem to increase the incidence of child labor. Children's school attendance is no different between SRI and non-SRI households. All of these findings appear robust to prospective selection on unobservables, as reflected by Rosenbaum bounds tests, and to strict or lax definitions of SRI use, based on partial or complete practice of SRI's four core components.

This failure to detect significant impact of SRI on total household labor income – replicated in Noltze, Schwarse and Qaim's (2013) study of SRI in Timor Leste – appears puzzling given the considerable boost to plot-level rice yields and profitability brought about by SRI. The system appears to increase the marginal physical product of land, effectively generating a positive technology shock for households that adopt SRI. But these impacts are not observed in total household labor earnings nor in child school enrollment and progress indicators. If there is no observable economic gain, why have farmers shifted from the conventional rice cultivation practices to SRI in the first place and only 18 percent of those who had experimented with SRI had disadopted by the time of our survey?

This puzzling result may reflect non-monetary preferences for on-farm work over off-farm work, perhaps due to travel costs, to economies of scope in joint production of rice and, for example, child care, or to social opprobrium associated with women's work away from home in this heavily Muslim area. Or this could reflect high valuation of leisure such that off-farm work merely supplements on-farm earnings to meet household cash needs as reflected in the budget constraint without SRI, and that households prefer to capture any Beckerian full income gains beyond that in the form of increased leisure rather than greater cash or in-kind income and resulting material consumption and/or investment. The use of SRI might also be a way for households to hedge against the risk of rice price volatility as enhanced yield due to SRI reduces the household's likelihood of purchasing rice on the market.[27] Unfortunately, the available data do not allow us to explore any of those hypotheses rigorously. Whatever the mechanism, the apparent productivity gains from SRI just do not appear in the income data, suggesting that total economic gains from SRI use are far smaller than the striking yield gains the method brings.

Such puzzling effects of seemingly-productive interventions are perhaps more commonplace than is often recognized. For example, Morduch, Ravi and Bauchet (2011) similarly find that the ultra-poor program in India increased beneficiaries' labor time and income in activities supported by the project, but at the same time reduced their income from other economic activities due to labor reallocation, resulting in changes in the composition of household income without solid net income gains. These findings nonetheless add an important new puzzle to the ongoing SRI controversy within the global rice research community. If one central objective of productivity growth is improvement in farm households' well-being, then we must establish more than the yield effects of SRI, or any novel system or technology. We need to uncover the broader impacts on income, educational attainment and other, broader welfare measures and reconcile puzzling findings such as those we report here among Indonesian SRI users.

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[1] The use of organic fertilizer and a mechanical rotary weeder are often included as core components of SRI (Stoop, Uphoff, and Kassam, 2002). Yet, akin to the setting in Noltze, Schwarze and Qaim (2012, 2013), these practices have rarely been adopted in the Indonesian locale we study, such that we exclusively focus on other four components.

[2] While a possible resolution to eliminate the impact of unobservable characteristics might be to employ an instrumental variable (IV) estimator instead of PSM, it is difficult to find good instruments. Moreover, IV estimator imposes a linear functional form assumption, which is more restrictive than PSM, which is invariant to functional form assumptions. Alternatively, a Heckman selection model could be used, but also needs identifying instruments and falls prey to selection on unobservables problems, as well as relying on rather strong distributional assumptions, where the unobserved characteristics of technology adoption and outcomes are jointly normally distributed with zero mean, constant variance and a covariance term (Mendola, 2007).

[3] We tried to control for unobserved farmers' skill by incorporating years of SRI experience, following Moser and Barrett (2006), which captures unobservable farmers' skill as well as learning by doing effects. However, since only 18% of farmers who had experience with SRI had disadopted it in our sample, years of experience proved difficult to balance between SRI users and non-users. Thus, we omit it in the results reported here in order to satisfy the balance condition of the matching estimator. Estimates that include

years of past SRI experience as a regressor and relax the balancing standard are qualitatively very similar.

[4] Contemporary Indonesian formal education consists of six years of primary education, three years of junior secondary education and three years of senior general secondary education or senior vocational secondary education, followed by a variety of forms of higher education in institutions such as academies, polytechnics and universities.

[5] There are also a few leasehold and land pawning contracts (called *Ta'gala*). *Ta'gala* is a system where a pawner temporarily transfers his cultivation right to the pawnee in return for a loan and can redeem these rights upon loan repayment without any interest charge.

[6] Because of the myriad valuation problems involved, non-cash input expenses, such as the imputed costs of family labor and machinery, are not deducted from the gross value of production less cash input costs. Self-consumed production is included as gross revenue by multiplying quantity consumed by market unit prices.

[7] On average, remittances account for approximately 89 thousand Rp per month.

[8] The data do not account for hired labor days because such information is unavailable.

[9] The exchange rate is 1 US dollar≈ 9050 Rp as of 2009.

[10] Ideally, the analysis would include a variety of additional welfare indicators, such as expenditures, health or nutritional status, and we could cross-check the income results against alternate measures. Unfortunately, such data are not available.

[11] No payments were made to respondents. This was a purely hypothetical exercise.

[12] Following Tanaka, Camerer, and Nguyen (2010), we enforced monotonic switching, so that no one went back and forth between Option A and B.

[13] This is an elicitation of risk preference after the decision to use SRI is made. Following the conventional literature, we implicitly assume that risk preference is time invariant and unaffected by experience with SRI. Because we find that SRI has had no effect on household income, it should also have had no effect on wealth. So we do not even have to assume constant (absolute or relative) risk preferences to maintain the assumption that risk preference is unchanged over time.

[14] We do not use an estimated cardinal value of risk preference, such as the midpoints of the imputed constant relative risk aversion (CRRA) intervals, because such a CRRA coefficient imposes strong assumptions on the shape of preferences and may not precisely reflect Arrow-Pratt risk preferences if there exist any threshold effects in underlying wealth dynamics (Lybbert and Barrett, 2011).

[15] If we allow the error terms to be correlated within a household (i.e., if we cluster standard errors at the household level), estimated standard errors increase such that the coefficient estimates for the size of plot, the number of plots a household operates, and the

risk averse dummy become statistically insignificant. Yet these modifications do not affect the treatment effects discussed in the main text, on which our core results turn.

[16] We acknowledge that using endogeneous variables can be also potentially a source of bias. To check whether final results with and without network variables change, we have omitted network variables in the propensity score function, constructed new matched pairs through kernel matching, and found that our headline results - significant effects on rice yield and income and negligible effects on total household income and child schooling - remain qualitatively unchanged.

[17] The dummy variable for at least one advisor experiencing SRI is proxy-reported behavioral information collected from sample farmers, which could reflect projection bias (Hogset and Barrett, 2008). As such, the causal effects of social learning cannot be identified by this propensity score estimation, and is left for future research.

[18] Those results are available in supplementary appendices. In total, we have 156 plot-level and 115 household-level treated on-support observations that are matched with 97 and 66 control observations, respectively. The maximum number of control observations used for matching is six for both. Since it is established that bootstrap standard errors are not appropriate with a nearest neighbor matching (Abadie and Imbens, 2006), we have estimated it with standard errors suggested by Lechner (2001).

[19] There is no significant difference in rice variety between SRI and non-SRI plots.The vast majority is dominated by “Membramo”, regardless of SRI status.

[20] The price of paddy is slightly higher for rice grown on SRI than non-SRI plots. However, since the seed variety, which is a decisive determinant of paddy price, is the same between SRI and non-SRI plots, and since SRI and non-SRI paddy are typically mixed and usually not sold separately in the market, the average prices are not statistically significantly different. This difference appears spurious.

[21] We also performed the sensitivity test proposed by Ichino, Mealli and Nannicini (2008) for cases of nearest neighbor matching. The baseline ATT point estimates proved very stable, never approaching zero even if the potential confounding factor is associated with large selection and outcome effects. Detailed results are available in supplementary appendices. Given the stability of our benchmark ATT result with respect to potential selection-on- unobservables and comparable endogeneity issues, we conclude that our estimated results are robust with respect to unobserved heterogeneity.

[22] See Appendix 2 for more detail.

[23] All explanatory variables pass the balancing test. This result is available in supplementary appendices.

[24] Less extreme effects might include lower grades or reduced cognitive or academic performance scores due to time reallocated from academic pursuits to on-farm work. We lack the data necessary to test such hypotheses, however.

[25] Although it is rare to observe child labor on farm in the area under study, our field observations suggest that children sometimes help simple work that does not require significant judgment and care, such as transplanting, harvesting, and drying (paddy).

[26] The variable is self-reported by parents. School-aged children include not only the head's biological children, but also any fostered or servant children.

[27] We thank an anonymous referee for pointing out this possibility.

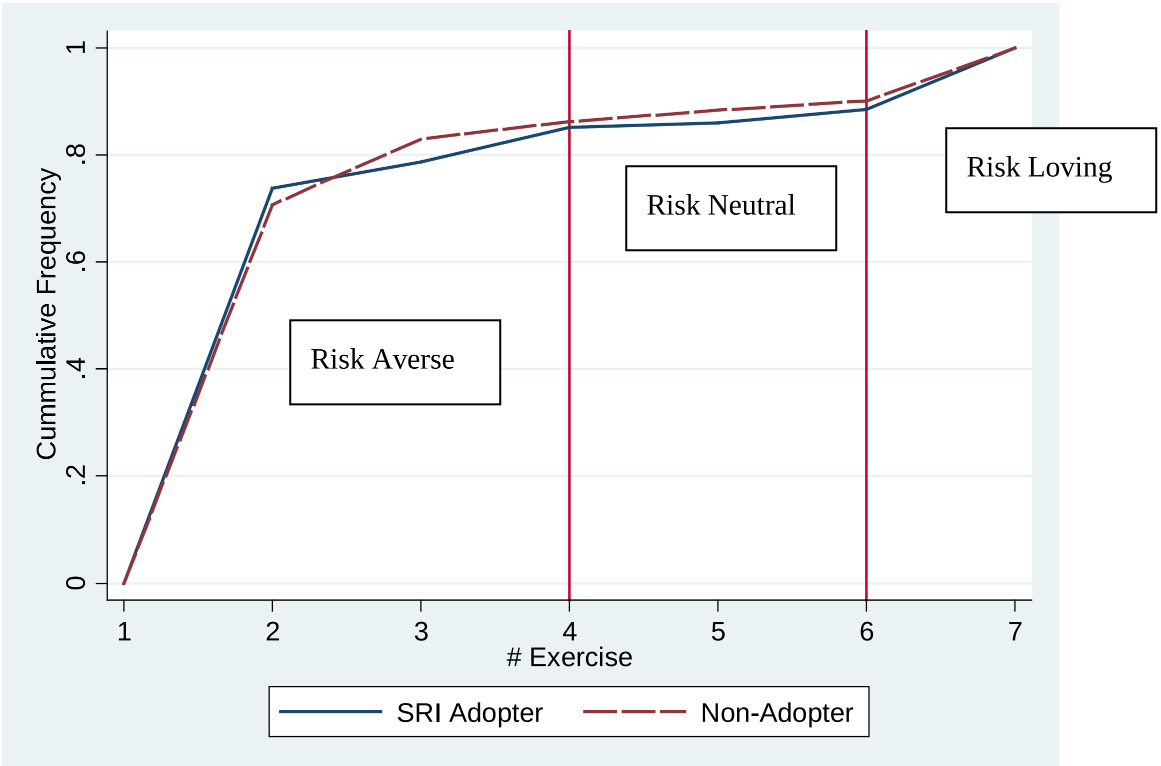

Figure 1. Cumulative proportion of respondents who switch to Option A

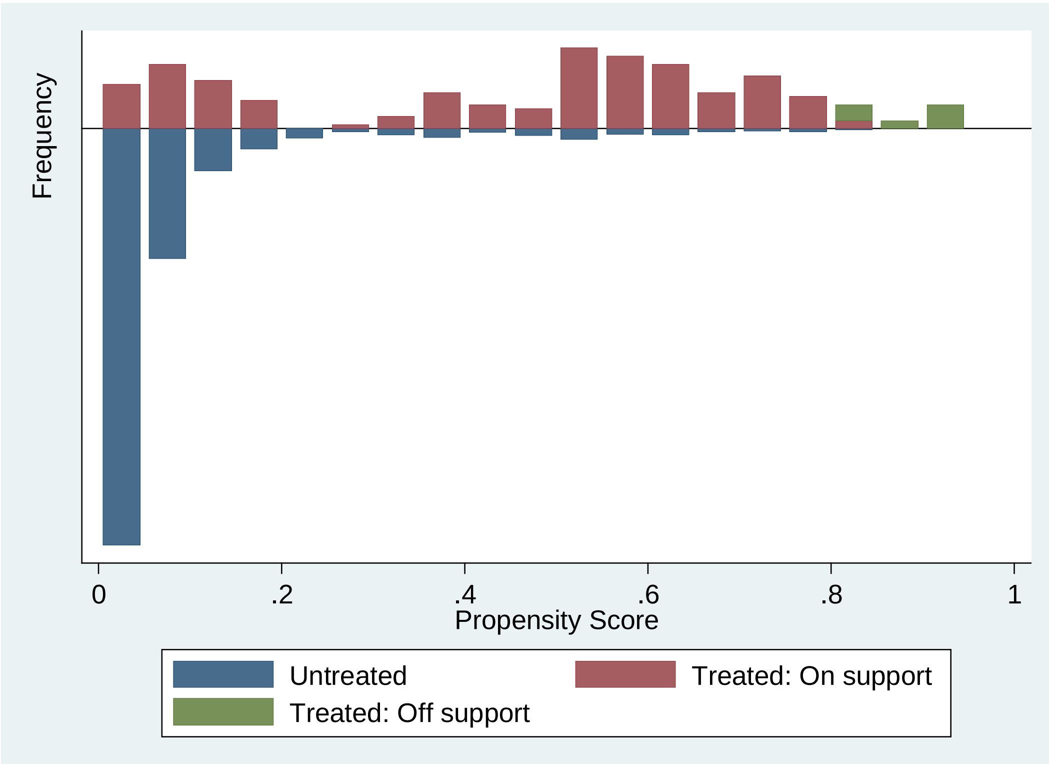

Figure 2. Histogram of propensity score

Table 1. Selected Household and Plot Characteristics

		Mean	s.d.
Household Characteristics			
Age of head	(years)	49.34	13.23
Female head	(%)	7.65	26.18
Completed Years of Education of Head	(years)	6.19	5.40
Household size		5.22	2.20
Male Household Members	(%)	48.01	16.52
# of Cultivated Plots		1.43	0.82
Total Land Size	(ha)	0.64	0.64
SRI Use	(%)	14.12	34.84
SRI Experience (unconditional)	(years)	0.71	1.91
SRI Experience (conditional)	(years)	4.31	2.80
SRI Disadoption (conditional)	(%)	18.67	39.09
Plot Characteristics			
Plot Size (ha)	(ha)	0.45	0.41
Irrigation	(%)	80.45	39.68
Own	(%)	73.54	44.13
Share	(%)	23.96	42.70
Other Tenure	(%)	2.50	15.61
SRI Use	(%)	13.98	34.69
Young Seedling (conditional)	(%)	97.62	15.29
Shallow Planting (conditional)	(%)	94.05	23.73
Sparse Planting (conditonal)	(%)	97.02	17.04
Intermittent Irrigation (conditional)	(%)	79.76	40.30
Full Application of SRI (conditional)	(%)	71.43	45.31
Full Application of SRI (unconditional)	(%)	9.98	29.99

Note: Sample size is 864 for household characteristics, and 1202 for plot characteristics

Table 2. Mean Difference in Outcomes by SRI Status

		SRI	Non-SRI	Diff
Plot level outcomes				
Paddy production per hectare	(ton)	5.50	2.95	2.54***
		(2.99)	(2.53)	(0.22)
Paddy production per personday	(kg)	132.10	75.68	56.40***
		(112.60)	(122.90)	(10.48)
Seasonal rice income per ha	(000 RP)	6673.70	2460.00	4213.70***
		(7616.40)	(4965.80)	(450.30)
Seasonal rice income per personday	(000 RP)	184.60	60.45	124.20***
		(344.50)	(174.30)	(17.78)
N		168	1034	
Household level outcomes				
Monthly total farm income	(000 RP)	732.50	238.80	493.70***
		(1042.10)	(618.20)	(67.75)
Monthly total off-farm labor income	(000 RP)	543.90	503.90	40.06
		(1235.40)	(1350.10)	(130.40)
Of which				
Monthly off-farm wage earnings	(000 RP)	398.10	272.30	125.80
		(1207.60)	(1056.80)	(105.40)
Monthly self-employed non-farm income	(000 RP)	145.90	231.60	-85.69
		(387.60)	(851.30)	(78.40)
Monthly total labor income	(000 RP)	1276.50	742.70	533.70***
		(1559.00)	(1547.20)	(151.30)
N		122	742	

Note: Standard deviations are in parentheses for means, while standard errors are in parentheses for the difference in mean.

Table 3. Summary of Risk Preference Elicitation Set-Up

Exercise	A	B		E[B]	E[B-A]	Risk Aversion Class if Choose A>B
		High	Low			
1	50000	75000	50000	62500	12500	Inefficient
2	50000	75000	45000	60000	10000	Risk-averse
3	50000	75000	35000	55000	5000	Risk-averse
4	50000	75000	25000	50000	0	Risk-averse to Risk-neutral
5	50000	75000	15000	45000	-5000	Risk-neutral to Risk-lover
6	50000	75000	5000	40000	-10000	Risk-lover
7 (Never Choose A>B)						Risk-lover

Table 4. Estimation Results of SRI Use Decision at the Plot Level (Probit)

VARIABLES	SRI
Dummy equal to 1 if plot is in upstream [a]	0.802***
	(0.238)
Dummy equal to 1 if plot is in midstream [a]	0.488**
	(0.199)
Dummy equal to 1 if plot is in downstream [a]	0.388
	(0.242)
Dummy equal to 1 if plot receive water directly from canal	0.947***
	(0.222)
Size of plot (ha)	0.243*
	(0.141)
Number of plots a household operates	-0.121**
	(0.052)
Dummy equal to 1 if plot is owned by a household	-0.168
	(0.134)
Dummy equal to 1 if a household head is female	-0.823***
	(0.294)
Age of household head (years)	-0.024
	(0.022)
Age of household head (years) squared	0.000
	(0.000)
Education of household head (years)	0.013
	(0.011)
Number of HH members age 6 and below	-0.330***
	(0.070)
Number of HH members age 15 and above	0.071**
	(0.032)
Number of HH members age between 6-14	0.026
	(0.073)

Proportion of male household members	-0.432
	(0.384)
Number of agricultural technology advisors	0.010
	(0.055)
Dummy equal to 1 if at least one technology advisor ever adopt SRI	1.843***
	(0.133)
Dummy equal to 1 if respondent is risk averse [b]	-0.425*
	(0.228)
Dummy equal to 1 if respondent is risk loving [b]	-0.002
	(0.269)
Constant	-1.274**
	(0.632)
Observations	1,202
Pseudo R^2	0.379

Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

[a] The omitted category is no irrigation. [b] The omitted category is risk neutral.

Table 5. Estimated Plot Level Impacts of SRI (ATT by Kernel Matching)

		SRI	Non-SRI	Difference	t-stat		Rosenbaum bounds critical level
Per hectare							
Paddy production	(ton)	5.54	3.37	2.17	6.69	***	3.6
Seasonal rice income	(Mill RP)	6.75	3.27	3.49	4.59	***	2.2
Family labor	(mandays)	62.75	46.72	16.03	2.56	**	1.2
Per personday							
Paddy production	(kg)	131.29	104.80	26.49	1.93	*	1.1
Seasonal rice income	(000 RP)	185.29	104.42	80.87	2.48	**	1.1

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. We use an Epanechnikov kernel with bandwidth of 0.06 and obtain standard errors by bootstrapping with 100 replications.

Table 6. Estimated Household Level Impacts of SRI (ATT by Kernel Matching)

		SRI	Non-SRI	Difference	t-stat		Rosenbaum bounds critical level
Monthly total farm income	(000 RP)	661.60	263.10	398.49	3.88	***	2.0
Monthly total off-farm labor income	(000 RP)	571.62	976.82	-405.21	-2.20	**	1.9
of which							
Off-farm wage earnings	(000 RP)	419.05	303.04	116.01	0.72		-
Self-employed non-farm income	(000 RP)	152.57	673.78	-521.21	-5.40	***	5.4
by gender							
Male	(000 RP)	237.67	147.58	90.10	0.89		-
Female	(000 RP)	333.94	829.25	-495.30	-3.64	***	2.8
Monthly total labor income	(000 RP)	1233.21	1239.93	-6.71	-0.03		-

Note: *** p<0.01, ** p<0.05, * p<0.10. We use an Epanechnikov kernel with bandwidth of 0.06 and obtain standard errors by bootstrapping with 100 replications.

Table 7. Estimated Impacts of SRI on Child Schooling (ATT by Kernel Matching)

	SRI	Non-SRI	Difference	t-stat
The proportion of school-aged children actually go to school	0.92	0.92	0.01	0.16
of which				
Male	0.99	0.95	0.04	0.65
Female	0.88	0.89	-0.02	-0.26
The proportion of school-aged children lagged behind	0.12	0.11	0.01	0.19
of which				
Male	0.01	0.07	-0.05	-0.79
Female	0.20	0.15	0.05	0.62

Note: *** p<0.01, ** p<0.05, * p<0.10. We use an Epanechnikov kernel with bandwidth of 0.06 and obtain standard errors by bootstrapping with 100 replications.

Table 8. Robustness Check: ATT by Full Adoption of SRI (by Kernel Matching)

		SRI	Non-SRI	Difference	t-stat	
Plot Level						
Per hectare						
Paddy production	(ton/ha)	5.07	3.38	1.69	4.64	***
Seasonal rice income	(Mill RP)	6.02	3.36	2.66	3.18	***
Family labor	(mandays)	67.69	46.33	21.36	2.59	***
Per personday						
Paddy production	(kg)	176.02	115.80	60.22	1.51	
Seasonal rice income	(000 RP)	118.50	106.91	11.59	0.82	
Household Level						
Monthly Total Farm income	(000 RP)	651.51	238.86	412.65	3.31	***
Monthly Total off-farm labor income	(000 RP)	533.46	1005.79	-472.33	-2.23	**
of which						
Off-farm wage earnings	(000 RP)	416.71	366.08	50.63	0.27	
Self-employed non-farm income	(000 RP)	116.75	639.71	-522.96	-5.07	***
by gender						
Male	(000 RP)	144.26	174.87	-30.61	-0.31	
Female	(000 RP)	389.20	830.92	-441.72	-2.81	***
Monthly Total labor income	(000 RP)	1184.97	1244.65	-59.68	-0.24	

The proportion of school-aged children actually go to school	0.94	0.90	0.04	0.80
of which				
Male	1.00	0.95	0.05	0.99
Female	0.88	0.84	0.04	0.51
The proportion of school-aged children lagged behind	0.06	0.12	-0.07	-1.21
of which				
Male	0.00	0.07	-0.07	-1.13
Female	0.12	0.20	-0.08	-0.95

Note: *** p<0.01, ** p<0.05, * p<0.10. We use an Epanechnikov kernel with bandwidth of 0.06 and obtain standard errors by bootstrapping with 100 replications.

Appendix 1. Balancing Test on Covariates (Kernel matching at the plot level)

	Pre-Match				Post-Match		
	Mean				Mean		
	SRI	Non-SRI	t-value		SRI	Non-SRI	t-value
Dummy equal to 1 if plot is in upstream	0.17	0.08	3.60	***	0.13	0.10	1.00
Dummy equal to 1 if plot is in midstream	0.61	0.48	3.17	***	0.64	0.61	0.50
Dummy equal to 1 if plot is in downstream	0.15	0.17	-0.38		0.15	0.18	-0.67
Size of plot (ha)	0.49	0.44	1.37		0.46	0.51	-0.85
Dummy equal to 1 if plot is owned by a household	0.68	0.74	-1.61		0.69	0.69	-0.04
Number of plots a household operates	1.80	1.87	-0.80		1.75	1.71	0.40
Dummy equal to 1 if plot receive water directly from canal	0.07	0.01	6.07	***	0.02	0.01	0.72
Dummy equal to 1 if a household head is female	0.01	0.08	-3.34	***	0.01	0.01	0.10
Age of household head (years)	47.69	49.06	-1.26		47.53	47.88	-0.23
Age of household head (years) squared	2450.60	2576.50	-1.11		2441.90	2477.40	-0.23
Education of household head (years)	7.94	6.21	3.85	***	8.06	7.85	0.34
Number of HH members age below 6	0.52	0.79	-3.57	***	0.54	0.61	-0.77
Number of HH members age 15 and above	3.67	3.74	-0.49		3.63	3.49	0.69
Number of HH members age between 6-14	0.76	0.75	0.04		0.78	0.90	-1.29
Proportion of male household members	0.49	0.48	0.50		0.49	0.47	1.18
Number of agricultural technology advisors	1.29	0.72	6.93	***	1.30	1.31	-0.07
Dummy equal to 1 if at least one technology advisor ever adopt SRI	0.73	0.10	23.45	***	0.71	0.70	0.00
Dummy equal to 1 if household is risk averse	0.75	0.82	-2.25	**	0.74	0.72	0.55
Dummy equal to 1 if household is risk loving	0.16	0.12	1.40		0.17	0.21	-1.06

Note: *** p<0.01, ** p<0.05, * p<0.10

Appendix 2. Estimation Results of Household SRI Use Decision (Probit)

Dummy equal to 1 if HH residential place is in upstream [a]	0.628**
	(0.307)
Dummy equal to 1 if HH residential place is in midstream [a]	0.325
	(0.269)
Dummy equal to 1 if HH residential place is in downstream [a]	0.183
	(0.303)
Total land size (ha)	0.236**
	(0.117)
Proportion of land under owed	-0.318**
	(0.151)
Proportion of irrigated land	0.241
	(0.310)
Number of plots a household operates	-0.122
	(0.099)
Dummy equal to 1 if a household head is female	-0.707**
	(0.303)
Age of household head (years)	-0.020
	(0.031)
Age of household head (years) squared	0.000
	(0.000)
Education of household head (years)	0.006
	(0.013)
Number of HH members age below 6	-0.246***
	(0.075)
Number of HH members age 15 and above	0.066*
	(0.035)
Number of HH members age between 6-14	0.076
	(0.082)
Proportion of male household members	-0.389
	(0.442)
Number of agricultural technology advisors	0.060

	(0.061)
Dummy equal to 1 if at least one technology advisor ever adopt SRI	1.883***
	(0.152)
Dummy equal to 1 if respondent is risk averse [b]	-0.264
	(0.274)
Dummy equal to 1 if respondent is risk loving [b]	-0.036
	(0.330)
Constant	-1.538*
	(0.883)
Observations	864
Pseudo R-squared	0.372

Note: Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.10

[a] The omitted category is no irrigation. [b] The omitted category is risk neutral.