Better Technology, Better Plots or Better Farmers? Identifying Changes In Productivity And Risk Among Malagasy Rice Farmers

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Abstract

In assessing the productivity gains of a new technology, it is often difficult to determine the extent to which observed output gains are due to the technology itself, rather than to the skill of the farmer or the quality of the plot on which the new technology is tried. This problem of attribution is especially important when technologies are not embodied in purchased inputs such as seed or machinery but result instead from changed farmer cultivation practices. Using data based on observations of farmers in Madagascar who simultaneously practice both a newly introduced and traditional rice production methods, we introduce a method for properly attributing observed productivity and risk changes among new production methods, farmers and plots by controlling for farmer and plot heterogeneity using differential production and yield risk functions. Our results help resolve several outstanding puzzling associated with observed low and incomplete uptake and high rates of disadoption of the new system of rice intensification (SRI) in spite of consistent, sharp yield increases on small farmers' fields without application of additional external inputs.

1. Introduction

Economic growth theory holds that technological change is the primary driver of long-run economic growth and improvements in human nutrition and well-being, as Nobel laureates Robert Solow and Robert Fogel have demonstrated. However, the mere development of a technology is clearly insufficient because its adoption by producers may be slow, partial, uneven and reversible across producers or absent all together. Agricultural and development economists—essentially beginning with Zvi Griliches (1957) — have therefore been extremely interested in the heterogeneity of responses to the introduction of new technologies and the implications for farmers and policy. Cross-sectional variation in the extent and rate of new technology adoption are often attributed to characteristics of the farmer or the farm, especially to differences in education, access to extension or financial services, risk preferences, and farm size (see Feder, et al. 1985

for a review). An important, underlying assumption of most analyses of technology adoption is that the new technology is unambiguously superior, so that adoption is optimal for all farmers. Even the most recent economic studies of technology adoption assume technological superiority, as in the justly-celebrated target input model of Foster and Rosenzweig (1995).[1]

While the technology adoption literature usually attributes adoption decisions to farm and farmer characteristics, the production economics literature tends to attribute the gains from adoption to the characteristics of the technology. Production economists working on agriculture have long relied heavily on researcher-directed experimental trials – both on station and on farm – in order to establish how different technologies change yields, yield risk, and labor productivity under alternative treatment designs. This method has worked extremely well in developing improved seed, fertilizer and machinery, the staples of historically unprecedented agricultural output growth over most of the 20th century (Evenson and Gollin 2002).

In recent years, attention has increasingly turned toward technological improvements that are not embodied in physical inputs such as seed, fertilizer or machinery, but that are instead reflected in farmer cultivation and natural resource management practices. When working with knowledge-intensive technologies, the correspondence between gains observed in researcher-directed trials and those experienced by actual farmers can be especially great. More specifically, farmer and farm heterogeneity in adoption patterns can introduce selection bias in observational production data, making it difficult to assess the true extent to which observed output gains can be accurately attributed to the new technology, since more skilled farmers typically are commonly the first to adopt improved technologies and often apply them on their best plots. This poses a methodological challenge for ex post evaluation of the productivity gains associated with knowledge-intensive technologies adopted by smallholders. This paper offers a means to disentangle the output effects – in both mean and variance – that are rightfully

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[1] Cameron (1999) is an important exception where disadoption is formally admitted as an option.

attributable to a new technology from those associated with farmer- and plot-specific characteristics.

We demonstrate our method using data from farmers in Madagascar who are experimenting with the System of Rice Intensification (SRI), an extremely promising, yet controversial, method of rice cultivation that was developed indigenously. Malagasy SRI adopters overwhelmingly use the technique on only a portion of their plots while they continue to grow rice using traditional methods on their remaining cultivable land. Using contemporaneous observations taken on both the new and old technologies for each farmer surveyed, we can isolate the true productivity and risk effects of SRI by controlling for farmer- and plot-specific effects using differential production and output risk functions. Moreover, our results shed considerable light on three puzzles surrounding SRI: why, given its well-demonstrated yield effects without requiring the purchase of any modern inputs, (1) have many farmers in areas of SRI dissemination not tried the technology? (2) Why have many farmers have abandoned SRI after experimenting with it? And (3), why do most farmers who continue to practice SRI nonetheless continue to use traditional methods on some of their rice fields?

The remainder of the paper is organized as follows. After a brief explanation of SRI and its adoption patterns in Madagascar in section 2, we describe the production data and present descriptive statistics in section 3. Section 4 discusses methodological issues and introduces our estimation strategy. We present our estimation results in sections 5 and 6, the former focusing on changes in mean output, the latter on production risk effects. We end with some concluding remarks in section 7.

2. Motivation: The SRI Puzzle

The System of Rice Intensification (SRI) has been researched, studied and debated since its development by a French missionary priest in rural Madagascar in the late 1980s. SRI is a set of principles based on the synergy among several techniques: seeding on a dry

bed, transplanting plants younger than 15 days old with one plant per hill, spacing of at least 20 x 20 cm – more commonly 25 x 25 cm or more – frequent weeding, and controlling the water level to allow for the aeration of the roots during the growth period of the plant (i.e., no standing water on the rice field). All of these components differ from traditional rice cultivation practices in Madagascar and elsewhere (Stoop et al. 2002, Uphoff and Fernandes 2002).

Other agricultural scientists question the science underpinning SRI and the sustainability of its yields (e.g., Dobermann 2003). Among other things, the limited water philosophy of SRI is unorthodox and controversial from the perspective of the international rice research community – both national agricultural research systems and the relevant international agricultural research centers – which has been relatively skeptical of SRI to date and slow to study it intensively. As a consequence, the conventional sequence of on-station development and trials, followed by researcher-managed, on-farm trials, and then carefully monitored farmer-managed, on-farm trials has not taken place with SRI. The technique was developed mainly through participatory, on-farm research by practitioners, with research scientists joining the process relatively late. As a consequence, basic questions surrounding SRI's true productivity and yield risk effects remain largely unanswered.

Nonetheless, limited research center and on-farm trials from several countries in Africa and Asia have shown that yields can consistently be doubled (or more) with few or no externally purchased inputs such as seed or chemical fertilizer (Uphoff et al. 2002). The remarkable observed increases in yields associated with SRI adoption have led many to believe that this method could dramatically improve the lives of the many poor small farmers in Madagascar – and other low-income rice-producing nations – who lack the liquidity to purchase modern inputs and for whom rice is both a staple and an important income source. In 2001, the *Financial Times* of London described SRI as a new "agricultural revolution" (Madeley 2001) and SRI has recently been taken up enthusiastically in other rice-producing nations – including Bangladesh, Cambodia,

China, Indonesia, the Philippines, Senegal and Sri Lanka – with many positive preliminary productivity results (Uphoff et al. 2002).

While some Malagasy farmers have adopted and continued to practice SRI, three perplexing facts call into question the oft-implied superiority of the method. First, adoption rates have been low. Second, rates of disadoption (abandonment) have been high. Third, most farmers who practice SRI continue to practice traditional methods (henceforth referred to as SRT) on some of their land, even after several years of experience with the new method. For example, Moser and Barrett (2003a) found that even in areas served by extension agents devoted exclusively to SRI, only about 15 percent of rice farmers practiced the method five years after its introduction and 40 percent of farmers trying the method had disadopted. The spread of SRI outside the areas where it was promoted is even lower. Figure 1 shows the distribution of SRI in Madagascar in 2001 based on a nationwide census of more than 1300 communes, the smallest administrative unit in the country. At least 62 percent show no use of SRI, and less than 3 percent of the nation's communes report SRI use by at least one quarter of the jurisdiction's farmers. Given SRI's origins in rural Madagascar and its oft-demonstrated productivity benefits, its slow and limited uptake by small farmers there remains a significant puzzle to many observers.

One mooted cause of low uptake is that SRI appears more labor intensive than traditional methods and requires better water drainage and management, although its initial adoption by a core group of farmers clearly indicates that these are not universally significant barriers to adoption. Moser and Barrett (2003a, c) show that poorer farmers with little land are much less able and likely to adopt SRI than richer farmers with more land. Farmers with more rice land and/or a strong non-rice income source were much more likely to try SRI. They speculated that poorer farmers lacking access to interseasonal credit cannot afford to reallocate labor away from wage employment that provides cash to meet immediate household consumption requirements during the hungry season (*soudure*), even if this reallocation would generate handsome yield increases several months in the future. By that hypothesis, a liquidity shortage (that prevents hiring labor

5

or reallocating family labor away from off-farm employment for cash wages) creates a family labor shortage that precludes investment in labor-intensive SRI. But those studies lacked detailed farm production data to verify that labor requirements indeed increased under SRI, especially early in the season. Moreover, they had less success explaining disadoption and the extent of adoption. In addition to establishing the true productivity and risk effects of SRI, using a more detailed production study of SRI adopters, we are able to shed some light on these three puzzles about SRI adoption in Madagascar.

3. Data

The data come from a study of the rice cultivation, water management practices and farm and farmer characteristics of 111 farmers contemporaneously practicing both SRI and SRT in three villages in Madagascar (Joelibarison 2001). The villages were purposively chosen based on their relative success with SRI. So the villages represent areas that are not only familiar with SRI, but also relatively successful in practicing the method. The program placement effects may well bias upwards the estimated productivity gains from SRI relative to farmers elsewhere in Madagascar, where water control, soil and market access conditions may not be as favorable. SRI farmers were randomly sampled within each village. The third puzzle of the preceding section – incomplete SRI use among adopters – is underscored by the fact that all of these farmers practice SRT as well as SRI on their rice lands. Cultivation using both methods provides us with a way to control for farmer- and plot-specific effects that typically bias cross-sectional productivity studies. Section 4 introduces our method for implementing such controls. The remainder of this section reports on key results from the sample descriptive statistics.

Farm and farmer characteristics
Table 1 describes key farm and farmer characteristics from the sample. These data are largely consistent with previous studies of SRI adopters using older and less detailed data (Moser and Barrett 2003a,c), which likewise found that adopters tend to be relatively well educated (with nearly 2 more years of education, on average), to be involved in

farmer organizations (50% of adopters versus 30% of non-adopters) and to own more rice land compared to nonadopters. Nationally, average rice land holdings are about 108 ares, as compared to nearly 134 ares in our sample. About 34 percent of the SRI farmers are net sellers of rice, which is roughly equal to the national average (Minten and Zeller 2000). [2]

Cultivation practices differ significantly between SRI and SRT fields, although other inputs are not very different in aggregate. Consistent with recommended SRI practices, the average age of the rice plant at transplanting is 10 days, versus 33 for SRT. Because of the water management requirements of the system, none of the SRI plots rely solely on rain run-off for water, while 7 percent of SRT plots are exclusively rainfed. Chemical fertilizer is not widespread on either type of field and mechanization (i.e. use of a tractor) is rare. Manure application rates are similar across SRT and SRI fields, as are the number of days of water shortage and the percent of fields on soils the farmers described as very rich.[3] While in the abstract, there may be valid concerns about plot-level selection effects biasing upwards estimated productivity gains due to SRI, in this sample, SRI and SRT plots appear very similar. The main within-farm difference is indeed in cultivation methods.

Unconditional land and labor productivity effects
Similarly consistent with earlier studies of SRI (Rajonarison 1999, Rakotomalala 1997), our data show that farmers' yields under SRI are nearly double on average their SRT yields and that labor productivity gains likewise appear high, on average (Table 2). However, even SRT yields are very high by Malagasy standards among this set of SRI adopters, with the mean SRT yield of 3.37 tons/hectare in this sample, more than 75 percent higher than national average rice yield (which includes improved methods such as SRI as well as SRT). This raises the question as to extent to which the remarkable

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[2] Comparisons with the data in the present study to others should be treated with some caution—80 out of the 110 farmers in the sample come from Ambatondrazaka, a major rice-growing region, where land holdings tend to be larger.
[3] African farmer subjective reporting of soil conditions has been widely validated for scientific accuracy. See, for example, the recent special issue of *Geoderma* volume 111, issues 3-4 (February 2003) on local soils knowledge for recent evidence on this point.

yield gains observed on SRI farmers' fields in Madagascar are due to the technology rather than to the aptitude of the SRI adopters themselves or to the quality of the plots on which SRI is cultivated.

Furthermore, both yields and labor productivity are considerably more variable under SRI than under SRT, both in terms of the standard deviation and the coefficient of variation. While more than doubling for nearly one-third of farmers, labor productivity actually falls for more than one-third of farmers in the sample. It is interesting to note that the fraction of farmers whose labor productivity fell with SRI is close to the proportion of farmers in another sample who disadopted (Moser and Barrett 2003a), hinting at a plausible explanation for observed abandonment of a technology that seems to uniformly increase rice yields.

In spite of increased variability in labor productivity and yields per unit cultivated area, SRI first order stochastically dominates SRT in terms of both yield per unit area cultivated and labor productivity, as can be seen clearly in Figures 2 and 3. SRT appears to hit a yield ceiling at about 5 tons/hectare while SRI easily doubles that yield ceiling. This would seem to suggest that SRI is an unambiguously superior technology.

However, stochastic dominance analysis assumes all farmers draw randomly from identical distributions, that the only differences in outcomes result from the technology selected and from chance. We suspect, however, that productivity differences are not, in fact, identically distributed across farmers and plots and that, as a consequence, comparison of SRI and SRT yields may be somewhat misleading as to the true productivity gains farmers might reasonably expect to enjoy from changing cultivation practices.

One way to test this hypothesis is to simulate SRI-SRT yield differences under the null hypothesis that differences in output realizations result purely from the choice of cultivation method and chance and then to compare the resulting simulated yield differences series with the observed yield differences series. We simulate yield

differences under the null hypothesis that farmer and plot-specific effects do not matter by randomly drawing (bootstrapping) a large number (n=1248) of observations from the observed, unconditional SRI and SRT yield distributions, pairing the series into pseudo-farms so as to estimate the simulated within-farm yield difference by subtracting the random SRT yield draw from its paired random SRI yield realization. We can then compare the bootstrapped distribution of random productivity differences against the observed distribution of actual productivity differences between SRI and SRT plots for farmers in our sample.

As shown in Figure 4, observed, farm-specific SRI-SRT yield differences plainly result from more than merely random shocks. The bootstrapped yield difference distributions first order stochastically dominate the observed yield difference distributions. Both are almost entirely positive – less than three (one) percent of actual (simulated) yield differences were negative – reflecting the productivity gains associated with SRI. Nonetheless, actual on-farm yield gains are consistently and considerably less than would be the case were choice of cultivation method the only systematic source of productivity differences. Hence the importance of multivariate control for factors that might otherwise confound identification of the true effects of the SRI technology on stochastic output distributions. In the next section, we introduce a method for doing estimating productivity differences with such controls.

Labor demands and experience with the new technology
While there is some dispute over the labor demands associated with SRI, most observers with whom we have spoken claim SRI increases labor demands in field preparation (especially leveling for water control), transplanting, weeding and daily water management. As discussed previously, this could matter importantly to farmers' perceptions of the likely benefits from trying (adopting) SRI or from continuing to practice SRI, if they have already experimented with the method. Those with a high marginal opportunity cost of time – due to cash constraints on the poorer end of the income distribution or due to relatively high wages or salaried employment on the richer end of the income distribution – might find SRI unattractive if it demands more labor

9

unless it generates sharply higher labor productivity. Within the community of SRI practitioners and researchers, one also hears many anecdotal claims that SRI's labor demands diminish rapidly with experience in using the technology.

These data indicate that most farmers with three or fewer years' experience with SRI indeed employ early season labor more intensively per unit area cultivated in SRI than in SRT. [4] Figure 4 depicts the median and span of the central half of the distribution (i.e., between the 25th and 75th percentiles) of farmers' observed early season labor use in SRI relative to SRT for different levels of experience with the new rice cultivation methods. The median farmer in his first three years with SRI uses 31.4 to 37.7 percent more labor per hectare in SRI. By the fourth year with SRI, the median farmer uses 4.2 percent less early season labor, improving to 10.9 percent less early season labor for those with five or more years' experience with SRI. There does appear to be mild support for the hypothesis that labor demands decrease with experience in using SRI.

Nonetheless, at all experience levels, a large share of farmers will have increased labor demands per area cultivated under SRI, with 30 percent or more at least doubling their labor application rate. This is consistent with previous findings that poorer, credit-constrained farmers choose not to adopt SRI due to increased early season labor demands that conflicts with their need to work off-farm for cash wages in order to buy food to meet immediate family subsistence needs and with findings that farmers with skilled or salaried off-farm employment are more likely to disadopt SRI after trying it (Moser and Barrett 2003a).

Some have suggested that experience should likewise improve productivity through learning by doing effects, that negative or low productivity gains may simply reflect a farmer's lack of experience with the technique. Because SRI requires significant changes in several different tasks throughout the growing season, Malagasy farmers often report that mastering the technique takes several years. Thus one might expect productivity

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[4] We define "early season" labor as including all labor for field preparation (e.g., leveling, plowing, irrigation, puddling), nursery preparation, transplanting, fertilizer application and weeding. It does not include labor devoted to guarding against birds or rats or to harvest.

differences to be low or even negative immediately after adoption, but to increase with farmer experience.

We test the hypothesis that there are "learning-by-doing" effects on productivity. Figure 5 and Table 3 show, however, that the proportion of farmers experiencing labor productivity losses with SRI cultivation does not fall significantly with experience, although median labor productivity does increase modestly. Of course, the rise in median productivity may well be attributable simply to attrition bias in these data, since those with extremely poor productivity under SRI would have been more likely to have disadopted SRI by the time of the survey, implying that those 2001 SRI farmers with significant past SRI experience are likely an upwardly biased sample of the farmers who first experimented with SRI several years earlier. In any case, learning by doing effects appear modest-to-negligible in these data.[5]

4. The Methodological Challenge

Establishing the superiority of one technology over another is difficult using observational data because of (both observed and unobserved) farmer and plot attributes that are unquestionably correlated with both farm productivity and the use of other inputs. Farmers who are especially productive with the new technology are likely relatively productive with the old technology as well because they have unobserved talents that positively affect productivity. Thus the failure to control for farm and farmer heterogeneity can lead to an overestimation of the returns to adoption of a new technology.

The gains to SRI will not only be overstated by failing to control for farmer differences when making comparisons across farmers, but also by failing to control for plot selection. Because SRI fields need good water control and drainage, farmers will practice SRI on

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[5] Moser and Barrett (2003c) similarly found that learning by doing effects were not significant in explaining area planted in SRI once one controls for household fixed effects.

the plots with these characteristics—characteristics that would produce higher rice yields under virtually any method. Similarly, if other inputs, such as compost (which is often recommended by SRI promoters) and mechanical weeders (which cannot be used on SRT fields if the farmer does not plant in rows), are used at a greater rate on SRI fields, then the yield gains may overstate the true total factor productivity gains due to SRI by capturing in part the effect of better complementary inputs.

One possible solution to this problem would follow the lead of the labor economics literature and use a Heckman selection model to control for the observable factors that lead to adoption so as to isolate the productivity gains. This can be an unsatisfactory solution, however, for several reasons. First, applied econometricians often have difficulty finding separate identifying instruments for the first-stage, selection equation and getting good predictions from it. As a consequence, controlling for the discrete choice to use the new technology is commonly highly imprecise and correlated with other regressors in the second-stage regression. Second, the selection model method can only control for observed farm and farmer characteristics, although it seems highly likely that commonly unobserved characteristics (e.g., aptitude, motivation, information access, timing of abiotic stresses due to temperature and water, etc.) play a significant role in agricultural technology adoption. Third, a Heckman-type sample selection model inherently discretizes a talent continuum into a binary adopt/disadopt variable and thereby cannot control for variation due to farmer- or farm-specific characteristics within the subpopulation of adopters. As a consequence such effects will typically be misattributed to the new technology, leaving a certain degree of "green thumb" bias in estimates of the productivity differences between the technologies. For example, in our sample, the correlation coefficient on SRI and SRT yields within the same farm equals 0.247, underscoring that there is significant correlation in productivity across technologies due to farm- and farmer-specific effects. A selection model could not control for these effects adequately.

There's a related problem if learning-by-doing effects are present. So long as productivity in using a method is increasing with experience, but at a decreasing rate as

12

hypothesized by Schultz, then comparing newly adopted technologies with long-established ones, lumping all adopters together irrespective of experience with the technology, fails to account for a farmer's learning about the new technology. This will tend to bias downward estimates of the productivity differences between the two technologies.[6]

Studies typically cannot control for these problems because they either do not observe both technologies in use by the same farmers at the same time – thereby permitting control for unobserved farmer attributes (the "green thumb" effect) –they do not observe how long the farmer has been using the new technology, or both. We can see that the preceding two concerns are an issue by running the simple OLS regression of crop yield under SRI on crop yield under SRT and years of experience with SRI. While such a simple regression is necessarily imprecisely estimated, Table 4 indicates that expected SRI yield is increasing in experience with the technology (although the estimated effect is not statistically significantly different from zero at conventional levels) and, most importantly, that once one controls for experience with SRI, a farmer's SRI yields increase essentially one-for-one with his SRT yields. This underscores the necessity of trying to separate farmer and farm-specific effects from those of the technology itself. The remainder of this section introduces a method for doing precisely that.

Differential Production Function Estimation

We can think of two different technologies. Each technology's production function has two sets of arguments. First, the vector **x** consists of r different production inputs under the control of the farmer, such as land, labor, animal traction and organic or inorganic nutrient amendments made to the soil. Second, the vector **z** comprises t distinct farmer- or farm-specific characteristics that are exogenous (in the short-term, at least) to decisions regarding input application rates. The **z** vector includes environmental conditions such as rainfall (quantity and timing), temperature, sunlight and density of pathogens and pests in the area, as well as plot characteristics, such as location on the

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[6] In revisions of this work, we plan to correct for selection bias in subsequent sections' multivariate estimation.

toposequence, water source and soil quality, and farmer characteristics, some of which are observable (e.g., experience with SRI, age, gender, education), and some of which are unobservable, such as farmer health and energy level, work ethic, farming aptitude, etc.

Farmers are concerned about production risk as well as expected output, so we represent these technologies in the Just and Pope (1977) tradition, permitting inputs to have either positive or negative marginal effects on production risk. The two technologies can be represented by the general functional forms

$$y_f = f(x,z) + h_f(x,z)^{\frac{1}{2}}\zeta_f \tag{1}$$

$$y_g = g(x,z) + h_g(x,z)^{\frac{1}{2}}\zeta_g \tag{2}$$

where the f and g subscripts reflect the technology employed, and ζ is a shock with mean zero and base variance σ^2 that is independent across the cross-sectional observations. This implies that the conditional expectation functions are f(x,z) and g(x,z), respectively. Using a first-order flexible approximation (i.e., first-order with interaction effects) to the true conditional expectation function for each technology for a given farmer i gives us

$$E[y_f]=\alpha_{f0}+\Sigma_{i=1}^{r}\alpha_{fi}x_{fi}+\Sigma_{i=1}^{r}\Sigma_{j=1\neq i}^{r}\beta_{fij}x_{fi}x_{fj}+\Sigma_{i=1}^{t}\gamma_{fi}z_{fi}+\Sigma_{i=1}^{t}\Sigma_{j=1\neq i}^{t}\eta_{fij}z_{fi}z_{fj}+\Sigma_{i=1}^{r}\Sigma_{j=1}^{t}\tau_{fij}x_{fi}z_{fj}+\varepsilon_f \tag{3}$$

$$E[y_g]=\alpha_{g0}+\Sigma_{i=1}^{r}\alpha_{gi}x_{gi}+\Sigma_{i=1}^{r}\Sigma_{j=1\neq i}^{r}\beta_{gij}x_{gi}x_{gj}+\Sigma_{i=1}^{t}\gamma_{gi}z_{gi}+\Sigma_{i=1}^{t}\Sigma_{j=1\neq i}^{t}\eta_{gij}z_{gi}z_{gj}+\Sigma_{i=1}^{r}\Sigma_{j=1}^{t}\tau_{gij}x_{gi}z_{gj}+\varepsilon_g \tag{4}$$

In these regression models, ε represents a mean zero, normally distributed, regression error term that is independently distributed across farms. The expected productivity gains attributable to the new technology are then reflected in the differences between the estimable parameters of the two production functions. For example, the difference α_{f0}-α_{g0} captures the absolute expected productivity difference irrespective of input levels and the difference in slope coefficients (e.g., α_{fi}-α_{gi}) reflects expected marginal productivity differences attributable to the new technology.

In estimating production functions, the types and quantities of inputs chosen are arguably endogenous, especially as the season progresses and farmers adjust input levels based on

weather, pest conditions, etc. Yet only the dual (cost or profit) estimation approach explicitly endogenizes this choice. Consequently, some analysts consider the dual approach preferable to primal (production function) estimation. However, in a setting such as rural Madagascar, where few inputs are transacted and there is considerable spatiotemporal variability in input and output prices, the errors in variables problem associated with estimating the dual cost or profit function is likely no less severe than the endogeneity problem associated with primal estimation. Moreover, endogeneity problems must now be plot specific since we control for unobserved farmer and farm specific effects. These effects are likely relatively modest, although they surely exist and must be kept in mind as one interprets results.

If we could observe all the elements of x and z, we could estimate the two production functions directly and then make those direct comparisons to recover the productivity differentials attributable to the new technology. Unfortunately, much of the key content of the z vector – attributes such as farmer aptitude, work ethic, the timing of rains, local pathogen and pest problems, etc. – rarely gets observed and recorded in farm production data. In so far as the observable x and z variables are correlated with the unobserved elements of z, unobserved heterogeneity will bias the estimated coefficients of the two production functions and will therefore also bias estimates of the productivity differentials of interest.

If individual farmers are simultaneously using both technologies, however, we can use farmer-specific fixed effects to effectively control for unobserved farm- and farmer-specific heterogeneity that is invariant across the technologies used by the farmer. If we separate out the unobservable and plot-invariant elements of z into another vector, w, and then subtract the modified equation (4) from the modified equation (3), we get the differential output function

$$y = \alpha_0 + \sum_{i=1}^{r} \alpha_i x_i + \sum_{i=1}^{r} \sum_{j=1 \neq i}^{r} \beta_{ij} x_i x_j + \sum_{i=1}^{t} \gamma_i z_i + \sum_{i=1}^{t} \sum_{j=1 \neq i}^{t} \eta_{ij} z_i z_j + \sum_{i=1}^{r} \sum_{j=1}^{t} \tau_{ij} x_i z_j + \varepsilon \qquad (5)$$

Where $y = E[y_f] - E[y_g]$ is the difference in expected output, $x = x_f - x_g$ reflects the difference in input application rates on plots using the two different technologies, $z = z_f - z_g$ reflects exogenous differences in the plots (e.g., soil type, source of water, or location on the toposequence), $\varepsilon = \varepsilon_f - \varepsilon_g$ is a mean zero, independent error term, and the parameters now directly estimate the marginal productivity differences between the two technologies. Importantly, note that all farmer-specific but plot-invariant characteristics, whether observed (e.g., farmer education, gender, age, prices) or unobserved (e.g., farming skill, timing of local biotic and abiotic stresses, capacity to motivate workers), have been differenced away to remove potential sources of bias. This is true as well of general environmental conditions such as rainfall, temperature, sunlight, and local pathogen and pest communities. Direct estimation of equation (3) therefore gives us consistent and unbiased estimates of the absolute and marginal productivity differences attributable to the new technology.

Differential production risk estimation

The conditional variance of the general functional forms specified in equations (1) and (2) are $V[y_f] = \sigma_f^2 h_f(x,z) = E[\varepsilon_f^2]$ and $V[y_g] = \sigma_g^2 h_g(x,z) = E[\varepsilon_g^2]$, respectively. We can compute the difference in output variance attributable to changing technologies as

$$s^2 = V[y_f] - V[y_g] = E[\varepsilon_f^2 - \varepsilon_g^2] = h(x,z) \qquad (6)$$

which can be estimated by subtracting the squared residuals from the two technology-specific production functions and then regressing those differences on the **x** and **z** vectors.[7] The technology-specific production functions take as arguments the regressors from the differential production as well as the observable farmer-specific effects (e.g., education, age, gender, regional dummy, etc.). We once again use a first-order flexible approximation to the true h function, estimating the differential yield risk function as

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[7] Alternatively, one could estimate only the $f_g(x,z)$ production function and take the difference between the squared residuals of the differential production function and two times the squared residuals from the estimated production function for technology g. A proof is available from the authors by request.

$$s^2 = \theta_0 + \Sigma_{i=1}^r \theta_i x_i + \Sigma_{i=1}^r \Sigma_{j=1 \neq i}^r \lambda_{ij} x_i x_j + \Sigma_{i=1}^t \varphi_i z_i + \Sigma_{i=1}^t \Sigma_{j=1 \neq i}^t \pi_{ij} z_i z_j + \Sigma_{i=1}^r \Sigma_{j=1}^t \omega_{ij} x_i z_j + \psi \quad (7)$$

where, and ψ is a mean zero, iid error term on the differential conditional variance regression. The parameters have similar interpretations with respect to production risk as the estimable parameters of equation (5) have with respect to mean output. Absolute differences between the technologies are reflected by the estimate of θ_0, while marginal differences are reflected in the slope and interaction parameters. Estimation of equations (5) and (7) thereby provides a method for establishing the differential effect of a new technology on expected outputs levels and production risk using data from farmers who practice both technologies simultaneously and controlling for the potential effects of better farmers or plots on observed yield differentials.

5. Differential Production Function Estimation Results

In implementing the method introduced in the previous section, we lose four observations due to incomplete data, leaving us with 107 observations from paired, randomly selected SRI and SRT plots, each pair cultivated by the same farmer. With such a small sample, precise estimation of the parameters of interest proves difficult, so we have dropped variables that initial estimation runs showed were of both extremely low statistical significance (p-values greater than 0.5) and very low magnitude, including animal traction, details on plot location along the toposequence, age of plants at transplanting, number of weedings, and a variety of interaction terms between variables.

Table 5 reports our regression results. The conditional mean equation exhibits quite high explanatory power, suggesting that observed output differentials across plots cultivated by the same farmer using different methods can indeed be explained reasonably well by this differential production function estimation method.[8] The results indicate that estimated absolute mean productivity is unconditionally much greater under SRI, as

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[8] Diagnostic tests for residual serial correlation, a common source of inflated goodness-of-fit measures, cannot reject the null hypothesis of no serial correlation at any reasonable significance level.

reflected by the sizable, positive and statistically significant constant estimate.[9] Expected output is also strongly increasing in the amount of land put into SRI rather than into SRT, i.e., SRI significantly boosts marginal land productivity.

By contrast, the point estimate on differential labor productivity is negative and not statistically significantly different from zero. SRI does not appear to boost marginal labor productivity in rice farming even though mean unconditional labor productivity increases. Since farmers typically have to pay a bit of a premium to hired workers when practicing SRI rather than SRT methods with which workers are more familiar, the lack of marginal labor productivity gains suggests that hiring additional workers to help with a switch to SRI does not pay. Several Malagasy farmers have told us precisely this and their claims are supported by the data. Given SRI's increased labor demands, previously shown, the attractiveness of SRI would seem to depend on the availability of surplus family labor having very low opportunity cost of time. This may well explain high rates of disadoption observed in previous studies, especially among SRI adopters with skilled or salaried off-farm employment, for whom the opportunity cost of time is relatively high.

Contrary to much informal speculation, experience with SRI seems to have, if anything, negative estimated effects on expected output. On its own, years of experience with SRI has a small, negative effect that is statistically insignificantly different from zero. Increasing SRI experience modestly dampens the increase in marginal land productivity attributable to SRI and has negligible effect on marginal labor productivity.[10] Given the attrition bias inherent to this sample – which should lead to overestimation of the effects

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[9] We reiteratre that the sample villages were purposively chosen to capture locations that had been relatively successful with SRI. We therefore suspect that this sample generates some upward bias in the estimated unconditional productivity gains associated with SRI because it we cannot control adequately for village-level factors related to water and extension availability, soil quality, market access, etc. Location-specific dummy variables had no statistically significant effect in an earlier regression, likely because all the sampled villages enjoy production conditions that are relatively favorable by Malagasy standards.

[10] The negative estimated interaction effect between SRI experience and area cultivated in SRI may reflect soil nutrient loss, given high yields and low rates of application of organic or inorganic fertilizers. Within the SRI community one sometimes hears concerns about the sustainability of the high yields observed on SRI plots under smallholder farming conditions. This topic merits more targeted investigation.

of experience on output – this seems reasonably strong, albeit perhaps surprising, evidence that learning by doing effects are not especially important with SRI.

The large positive estimated output effect of employing SRI rather than SRT methods on plots with richer soils reflects that some observed productivity effects are due to plot selection. SRI likewise increases the marginal productivity of manure applied to rice fields.[11] Absence of good water control reduces the expected productivity gains from SRI, as reflected in the negative coefficient estimate on the variable for days of water shortage experienced on the plot. Since careful water management – reducing water demands appreciably, in many cases – is a cornerstone element of the SRI method, it comes as little surprise that good water control increases the relative productivity gains associated with switching from traditional rice cultivation in fields with standing water. These results underscore that part of the output gains commonly observed in SRI farmers' fields are likely due to plot-specific effects related to the relatively high quality of the fields in which SRI farmers have been experimenting with SRI and that these plot-level effects seem to attenuate adverse labor productivity effects attributable to SRI itself *ceteris paribus*.

These estimates permit us to decompose the unconditional productivity gains observed in descriptive statistics into gains due to (i) "better technology", reflected in the estimated absolute productivity differences plus the marginal productivity differences evaluated at the sample mean variable input levels, (ii) "better plots", manifest in the estimated differences due to richer soils and superior water availability on SRI plots relative to SRT plots, and (iii) "better farmers", the observed and unobserved farmer-specific effects that we differenced away in estimating the differential production function. We can recover this latter effect by computing the mean output gain attributable to switching a field from SRT to SRI by taking the mean yield difference from Table 2 and multiplying by mean land size in SRI to get mean additional output from putting land into SRI, and then

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[11] Chemical fertilizer application was omitted from the regression because it was used by so few farmers (<10%) and because its use is likely endogenous. Manure application, on the other hand, is more likely a function of the number of cattle owned and is typically applied earlier in the season than chemical fertilizers in this system.

subtracting off the regression-based estimates of (i) and (ii) to recover the omitted farmer- (not plot- or technology-) specific component to observed productivity gains.

Table 6 reports the estimated decomposition of output gains associated with SRI by source. As was reasonably obvious from the meager differences between SRI and SRT plots (Table 1), plot-specific characteristics associated with soil quality and water control account for only a negligible portion of observed gains, about one percent. Most of the observed output gains, 56 percent, appear to be due to farmer-specific effects. The technology adoption literature consistently finds that initial adopters are better farmers overall. These data suggest that those who fare best with new SRI methods are similarly better farmers than those adopters who enjoy lower (or no) productivity gains from changing cultivation practices.

The productivity gains from SRI are quite real and substantial. Mean output gains are 87.8% on plots cultivated using SRI, relative to putting the same plot into SRT. Even with only 43 percent of the observed productivity gains truly attributable to SRI practices, the estimated output gains due just to switching to SRI are 37.4 percent. Straight comparison of average yields may overstate the productivity gains from SRI, but they appear very real nonetheless, at least among small farmers in Madagascar.

6. The Yield Risk Implications of SRI

As we observed in the descriptive statistics, SRI yields and labor productivity are considerably more variable than those of SRT. This raises the question of whether puzzlingly low rates of SRI adoption might reflect in part risk avoidance behavior by smallholder farmers. If the expected output gains attributable to the SRI technology itself – taking away the gains that are attributable really to plot- or farmer-specific effects – are somewhat less than they seem in the unconditional statistics, then one can readily imagine increased risk weighing heavily on farmers, perhaps especially the smallest

farmers who previous studies suggest are the least likely to adopt SRI (Moser and Barrett 2003c).

The estimation results (Table 5) reveal that there is indeed a big increase in yield risk due to SRI. Morever, yield risk appears to increase sharply and statistically significantly in the amount of land devoted to SRI. The marginal risk effect associated with labor allocated to SRI is negligible and statistically insignificantly different from zero. Increased experience with SRI does appear to reduce the increased yield risk associated with this cultivation method. Although none of the experience variables is individually statistically significantly different from zero,[12] the point estimates are negative and the relevant p-values are sufficiently low to suspect that experience truly reduces yield risk but that our sample is simply too small to estimate this effect precisely.

The additional yield risk associated with SRI may explain why some more risk-averse farmers do not adopt the method at all and why most adopters do not put all their land in SRI. Newbery and Stiglitz (1981) offer a simple, back of the envelope method for estimating household's willingness to pay for risk reduction.[13] By this method, farmers should be willing to take on additional yield risk so long as their risk aversion, as measured by the conventional Arrow-Pratt coefficient of absolute risk aversion, A, is less than twice the quotient of the change in mean divided by the change in variance. Using the same decomposition method we employed in the previous section with respect to mean output changes to recover the change in output variance attributable to SRI, rather than to plot-, experience- or farmer-specific effects, we find that the minimum A is approximately 0.163, well below most published estimates of farmer risk aversion, which are typically in the 1.0-3.0 range. This suggests that only farmers who are essentially yield risk neutral or who have (financial or nonfinancial) means to insure against yield risk would likely be willing to adopt and stick with SRI.

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[12] We need to do joint significance testing of the effects of experience in both the mean and variance equations for the next revision.

[13] Newbery and Stiglitz (1981) derive this result by setting certainty equivalent utility equal to expected utility, then taking a second-order Taylor expansion and rearranging terms.

Among the set of adopters, moreover, risk management considerations may well make it rational to limit the extent of adoption of SRI because yield risk increases more rapidly than expected output as one increases land in SRI. Similarly, since experience with SRI decreases yield risk at a much faster rate than it decreases expected output, adopters' willingness to use SRI will increase with experience as the mean-variance tradeoffs become more attractive over time.

7. Conclusions

The rise of knowledge-intensive technologies poses a challenge to those who seek to establish the true productivity gains associated with a new production method. Imperfectly observed farmer and farm heterogeneity can introduce selection bias in observational production data, making it difficult to assess the true extent to which observed output gains can be accurately attributed to the new technology, since more skilled farmers typically get more out of any technology – new or established – and are commonly the first to adopt improved technologies and often apply them on their best plots. This situation describes the challenge of evaluating SRI, an extremely promising new rice cultivation method developed in rural Madagascar that is disseminating rapidly to other tropical rice-growing regions.

In introducing an econometric method to disentangle the output effects – in both mean and variance – that are rightfully attributable to a new technology from those associated with farmer- and plot-specific characteristics, we find that SRI indeed generates handsome productivity gains for small farmers in Madagascar. Nonetheless, simple yield differences greatly overstate those gains, most of which appear attributable instead to farmer-specific effects. Straight comparisons of unconditional yield estimates therefore suffer what might be termed "green thumb bias". Little of the observed output gains from SRI are due to plot-specific attributes such as better soils or water control, but more is due to better farmers than to a better technology, although both factors are plainly at play.

Our results also help to answer three puzzles concerning SRI adoption patterns in Madagascar. Why, given striking yield increases consistently observed on SRI fields, do we not see more widespread adoption of SRI across or within farms and why do we observe significant rates of disadoption by those who have experimented with the method? One part of the answer seems to revolve around labor availability and productivity. Increased early season labor demands may indeed make SRI unattractive to those for whom the opportunity cost of labor time is very high, such as the very poor who depend on wage labor early in the rice season to meet short-term subsistence needs or those with skilled or salaried off-farm employment, especially because SRI seems to have no significant effect on marginal labor productivity in rice cultivation. Its gains come principally from increased marginal land productivity. While yields increased for nearly all farmers under SRI, labor productivity gains varied widely, with more than one third of farmers actually experiencing losses in kilograms harvested per (non-harvest) day worked.

The other part of the answer to the extant puzzles of SRI adoption seems to lie in the increased yield risk associated with SRI. Even at low levels of risk aversion, SRI may increase farmer risk exposure unacceptably for those unable to insure against prospective crop losses. These risk effects dampen reasonably quickly as farmers accumulate experience with the method, so those who find it attractive to adopt initially will typically find SRI increasingly attractive over time in risk-return tradeoff terms.

On average, SRI increases rice productivity on small farmers' fields independent of the abilities of the farmer or the quality of the field. Yet it is easy to exaggerate the method's productivity benefits and it is not unambiguously superior for all farmers. Understanding that some farmers may not stand to benefit from even seemingly strongly superior methods such as SRI implies that — rather than blaming farmers for their failure to adopt a promising new technology— policy makers and extension services aiming to stimulate increased rice productivity may need to identify alternative ways to improve field conditions and current cultivation practices or alternative sources of income.

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Table 1: Farm and Farmer Characteristics

Farmer Characteristics

Mean age of farmer	40.93
(Standard deviation)	(12.05)
Percent male	87%
Percent of farmers belonging to farmer organization	51%
Percent of farmers with no education	4%
Percent of farmers with high school education or better	29%
Mean months of *soudure*	2.63
(Standard deviation)	(2.84)

Farm Characteristics

Mean total rice area (ares)	132.74
(Standard deviation)	(132.87)
Percent of Rice land in SRI	46%
Percent with tractor	2%

SRI Fields

Mean years of SRI experience	2.52
(Standard deviation)	(1.86)
Mean days of water shortage in field	42.70
(Standard deviation)	(68.43)
Percent of fields on rich soils	29%
Percent using manure on SRI fields	21%
Percent using chemical fertilizer on SRI fields	10%
Percent with rainfed fields	0%

SRT Fields

Mean years of rice growing experience	17.87
(Standard deviation)	(12.97)
Mean days of water shortage in field	41.09
(Standard deviation)	(74.58)
Percent of fields on rich soils	27%
Percent using manure on SRT fields	21%
Percent using chemical fertilizer on SRT fields	7%
Percent with rainfed fields	7%

Table 2. Productivity of land and labor

	SRI		SRT		Mean	Median
	Mean	Standard Deviation	Mean	Standard Deviation	Percent change	Percent Change
Yield (kg/hectare)	6327	1795	3368	506	88	85
Labor Productivity (kg/day)	9.5	14.6	5.5	4.4	73	52
Non-harvest labor (days/hectare)	1280	1052	1074	1075	19	27

Table 3. Labor and land productivity by years of experience

Years of Experience	Mean percent of land in SRI	Median percent yield increase	Median percent labor productivity increase	% of farmers with negative productivity gains with SRI	Number of farmers
1	36%	88%	62%	33%	42
2	38%	61%	12%	45%	22
3	30%	101%	59%	33%	21
4	28%	94%	99%	33%	9
5+	42%	101%	159%	27%	15
All	36%	85%	52%	35%	109

Table 4: SRI-SRT yield correspondence

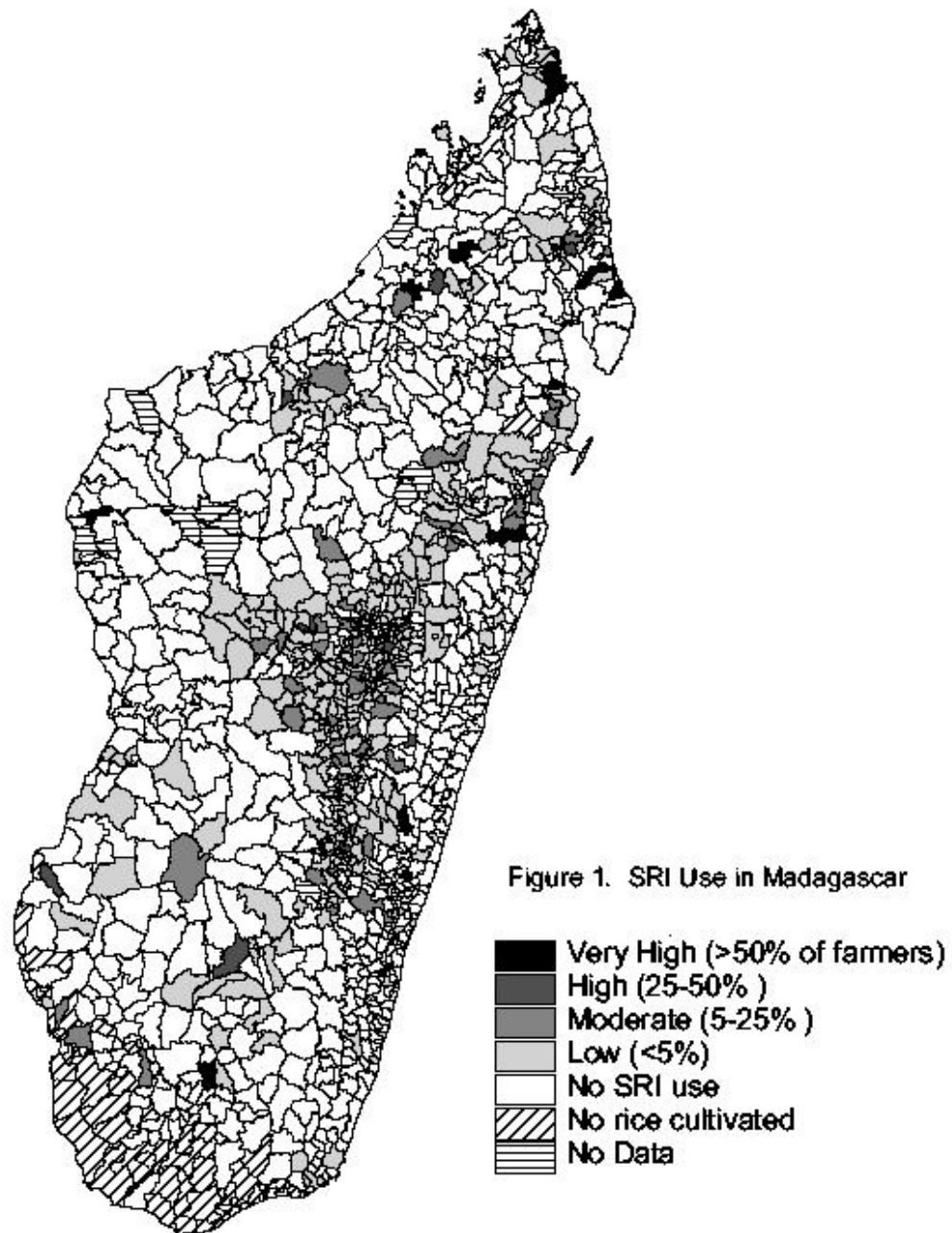| Dependent variable = SRI yield (kg/ha)	Point Estimate	Standard Error
Intercept	2691.41	1163.72
Years SRI experience	101.13	87.74
SRT yield (kg/ha)	1.02	0.33
N= 110, R^2 = 0.088		

Table 5: Estimated difference in rice output mean and variance under SRI

Dependent variable = SRI-SRT rice output difference, in kilograms	Difference in E(output)		Difference in V(output)	
	Point estimate	Standard error	Point estimate	Standard error
Constant	1823.78**	470.90	2295110.00**	1309114.00
Land (ares)	58.60**	9.73	40186.64**	23773.16
Non-harvest Labor (days)	-0.27	0.58	-274.80	1066.38
Experience (years)	-22.61	134.51	-161854.50	207668.10
Rich Soils (dummy)	764.52	525.64	79863.15	609409.10
Manure application (kg)	1.02**	0.36	414.25	782.79
Days of water shortage	-5.59	3.50	-9039.92	5905.03
Land x Experience	-4.62*	2.43	-7249.21	4787.33
Labor x Experience	0.03	0.17	66.25	311.65
R-squared	0.87		0.26	

* (**) indicates statistical significance at the ten (one) percent level

Table 6: Decomposition of output gains by source

Percent share of mean SRI output gains due to …	
SRI Method	42.6%
Plot-Specific Characteristics	1.2%
Farmer-Specific Effects	56.2%

Figure 1. SRI Use in Madagascar

Very High (>50% of farmers)
High (25-50%)
Moderate (5-25%)
Low (<5%)
No SRI use
No rice cultivated
No Data
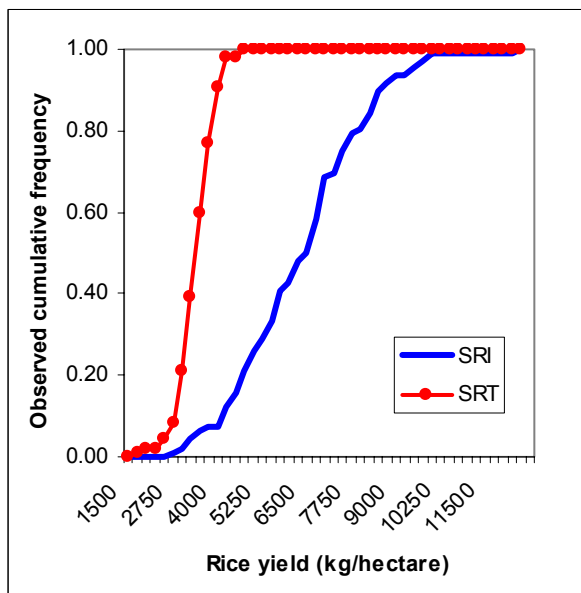
Figure 2: Yield distributions
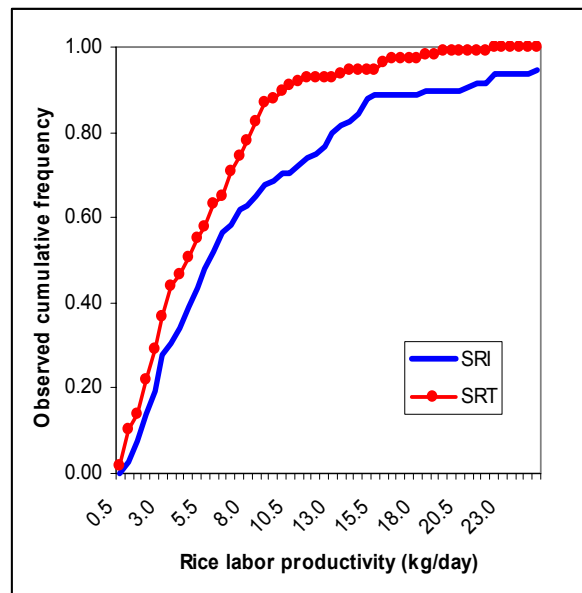
Figure 3: Labor productivity distributions
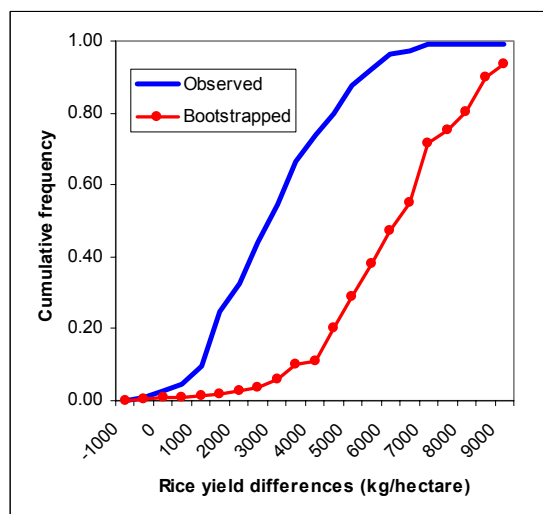
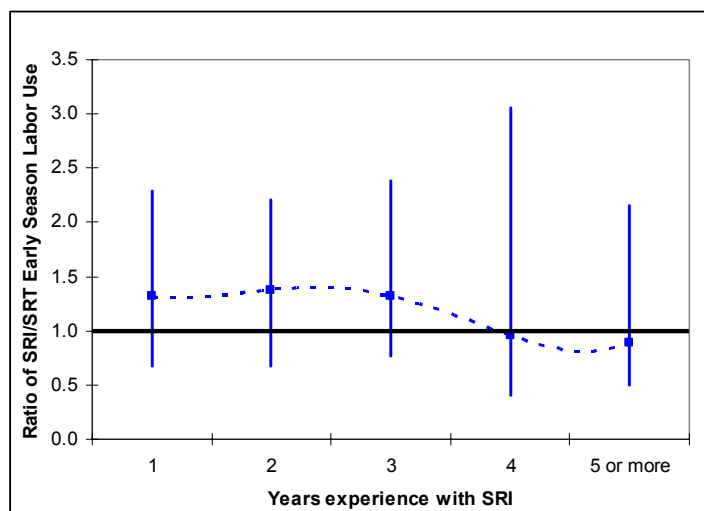Figure 4: Actual versus bootstrapped SRI-SRT yield differences
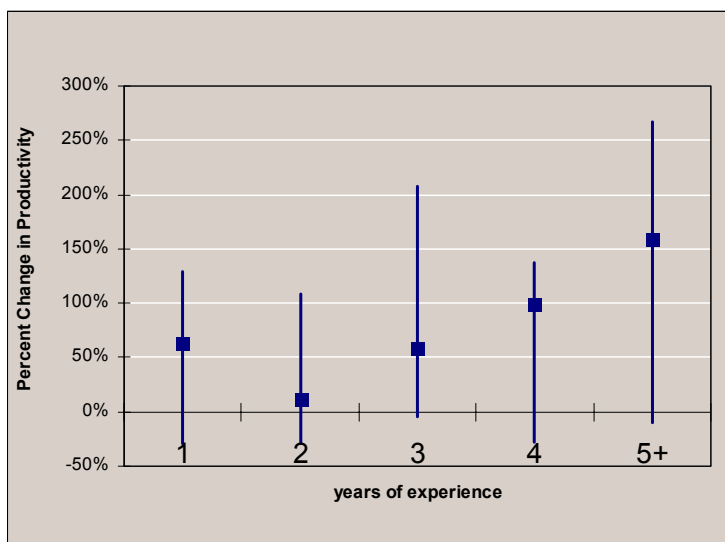
31

Figure 5. Median and span of labor use ratio

Figure 6. Median and span of the percent change in labor productivity