# Complementarities and differences in adoption: an application of hazard models to two technologies in Madagascar

J.S. Butler
University of Kentucky

Christine Moser
Western Michigan University

*Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2010 AAEA, CAES & WAEA Joint Annual Meeting, Denver, Colorado, July 25-27, 2010.*

*Corresponding author: christine.moser@wmich.edu.
Department of Economics
Western Michigan University
1903 West Michigan Avenue
Kalamazoo MI 49008-5330

# Complementarities and differences in adoption: an application of hazard models to two technologies in Madagascar


## Abstract

This paper explores the adoption of two agricultural technologies, how their patterns of adoption differ, and the relationship between them. The first technology, the System of Rice Intensification, has been studied previously and high rates of disadoption were observed in some areas. The second technology is off-season cropping, the practice of growing crops (primarily potatoes) in the rice fields during the winter season after the rice harvest. The rates of adoption of off-season cropping were much higher than for SRI and very little disadoption was observed. Through this study we are trying to understand the factors that might explain the differences in adoption and how the adoption of and experience with one technology affects the likelihood of adoption of the other. Our analysis uses hazard models, which have only recently been applied to technology adoption. Findings suggest that both methods increase the likelihood of adopting the other, and off-season crop adopters were less likely to disadopt SRI. Liquidity constraints appear to be more of an obstacle to SRI adoption, suggesting that this might help explain the relative success of off-season cropping.


## 1. Introduction

This paper explores the adoption of two agricultural technologies, how their pattern of adoption differs, and the relationship between them. The first technology, the System of Rice Intensification (SRI), has been studied previously and high rates of disadoption were observed in some areas. The second technology is off-season cropping, the practice of growing crops (primarily potatoes) in the rice fields during the winter season after the rice harvest. The rates of adoption for off-season cropping were much higher than for SRI and very little disadoption was observed.

These two methods are distinct and there is no direct relationship between them and no obvious logical sequencing. However, there are potential complementarities between the two technologies. First, they do not compete for the farmer's time because they are grown at different times of the year. Second, revenue from one could potentially fund the adoption of the other. Adoption of SRI, for example, could generate extra income from rice at harvest, which would provide liquidity to purchase seed and fertilizer for off-season crops. Finally, fertilizer use for off-season cropping is more common than for rice, but because they are practiced on the same fields, the fertilizer could also provide a boost in rice production. However, it might simply be the case that certain farmers are more likely to adopt new techniques in general and the complementarities are unimportant.

Hazard models are well-suited to the context described above, yet they have not been widely used in the technology adoption literature. They can control for unobserved farmer heterogeneity, allow us to study the sequence of adoption of these two techniques, and include time-varying variables in our estimation. Our data come from a sample of 317 rice farmers in Madagascar. Based on both farmer recall and extension records, the data set includes information on SRI and off-season crop use between 1994 and 1999. We explore the effect of one technology on the adoption of the other by looking at both experience with the technology and its use in the prior season. We also examine the effect of extension presence and household and plot characteristics to better understand the diverging adoption patterns observed for the two technologies.

The paper is organized as follows. The next section briefly discusses the advantages and disadvantages of hazard models in the context of technology adoption. Section 3 describes the data and background. Section 4 presents the estimation results and section 5 provides some concluding remarks.

## 2. Applying hazard models to technology adoption and alternatives

Technology adoption studies have long relied on logit and probit models. This approach is intuitive because for many technologies and studies, adoption is simply measured in discrete terms—a farmer either has or has not adopted. However, there are several important disadvantages to this approach. First, it ignores the timing of adoption because the researcher typically is looking at a single point in time at who is currently using the technology and who is not. Adoption is a dynamic process; it has long been recognized that early adopters differ from later adopters and current non-adopters may eventually adopt. A probit or logit estimated, for example, on a five year period cannot be used to evaluate the effects over time that speed or slow adoption. Second, these methods are quite limited in their ability to control for farmer heterogeneity, even when panel data is available.

Hazard models have several advantages over logit and probit models. Hazard models take advantage of more information, namely the timing of adoption, which cannot be exploited in logit or probit models. Hazard models allow continuous-time analysis regardless of the periods used in the data themselves. This means that probabilities can be predicted over a period of one year regardless of the number of periods observed. They can also accommodate time-varying independent variables, if available.
Finally, hazard models can be used to control for unmeasured heterogeneity. That matters greatly in principle because over time, unmeasured factors encouraging long duration (low probability of adoption) dominate the remaining sample. That implies that time appears to slow the adoption process when time might be irrelevant. The changing pool of those who have not yet adopted is conflated with passing time. Concern over unmeasured heterogeneity in technology adoption studies has led to calls for greater use of panel studies (Doss 2004). Thus a further advantage of hazard models is the ability to control for unmeasured heterogeneity without the need for a full panel data set. While this is not the same as controlling for farmer fixed effects, since, as described above, hazard models can control for unmeasured differences in the pool of adopters and non-adopters over time, this is still an important improvement over standard cross-sectional approaches.

The main disadvantages of hazard models are unfamiliarity and attendant difficulty in interpreting and explaining the coefficients, marginal impacts, and expected durations, and the inability to include endogenous variables or correct for selection bias in any straightforward way.[1] The net advantages have lead to a history of the use of hazard models in medical, social, and economic research. To date, few published studies in agricultural economics have utilized hazard models in empirical work. Abdulai and Huffman (2005), for example, apply a hazard model to agricultural technology adoption using a proportional hazard assuming a Weibull distribution applied to cross-bred cow adoption in Tanzania.

A secondary issue in our study is that we are looking at the adoption of two technologies. There are several technology adoption studies that have studied the sequencing of technologies (for example, Leathers and Smale 1991, Dorfman 1996, Ersado et al. 2004). Leathers and Smale (1991) and Dorfman (1996) are primarily concerned with technology "bundles", closely related technologies used on the same crop—fertilizer and seed packages, for example. Dorfman (1996) and Ersado et al. (2004) apply multinomial probit and logit models, respectively. However, as in the binary choice models, we would lose some of our time-varying information in this approach, would not be able to control for unobserved heterogeneity and would not directly be able to test the effect on one technology on the adoption of the other.

Our econometric approach is to estimate separate hazard models for SRI and off-season cropping, including adoption information of one in the estimation of the other. We will look at both the effect of use of the other technology in the previous season as well as the number of years of experience using it. The former might be seen as having more of a liquidity effect, while the latter might better capture learning. Finally, we will compare our hazard models to panel and probit models. Panel models allow us to control for farmer fixed effects, but the limitation is that in the present context few variables are time-varying. By comparing the three models for both technologies we hope to both demonstrate the advantages of hazard models and explain the different adoption patterns of the technologies in our study.

---

[1] Additional concerns are sometimes raised because hazard models usually assume that everyone eventually adopts, but this is not required. The hazard is the conditional probability of adoption at a given time, and if the integral of the hazard diverges, the probability of eventual adoption is one, i.e., adoption is certain. The integral of the hazard is not required to diverge for any specification of the hazard model, however, and the hazard can asymptote to zero, meaning that after some point, adoption is highly unlikely. Those who are certain to adopt eventually are movers and those who will not adopt are stayers, and this is a mover-stayer model. The difficulty with this is not in the specification, estimation, or interpretation of conditional effects, which depend in no way on eventual adoption, but rather in the expected duration, which is very long and in fact infinite. The calculation of expected duration makes no sense in that case. The alternative is to compute an expected duration given some allowed length of time, e.g. twenty years, then compute elasticities of this expected duration with respect to explanatory variables.

## 3. Background and data

*The System of Rice Intensification*

The intensification of agricultural production is essential in Madagascar for increasing rural incomes, improving food security and providing an alternative to extensification into environmentally sensitive areas. Because rice is the major staple crop and upland rice cultivation is the major cause of deforestation, intensification of lowland rice production has been a major focus of many development interventions. The System of Rice Intensification[2] (SRI) is a method that has been promoted and closely followed in Madagascar for almost twenty years. The method has since been introduced in other countries including China, India, Indonesia and Cambodia and has even received attention in the popular press (for example, Broad 2008, Surridge 2004).

The System of Rice Intensification (SRI), developed in Madagascar with the help of Malagasy farmers, requires no chemical fertilizers or pesticides and can be practiced with local seed varieties. The method can double or triple rice yields in smallholder farmers' fields, albeit from a low base (average yields of 2 t/ha or less). Several studies have shown that by using a combination of techniques requiring an estimated 25-65 percent more labor than traditional methods, farmers can increase yields more than 100 percent—and reports of increases of more than 300 percent are not unusual (Randrianasolo 1995; Rakotomalala 1997). These yields appear to be sustainable over time. Given poor Malagasy farmers' heavy dependence on rice for both income and household consumption and the difficulty accessing chemical fertilizer and improved seed, SRI would appear to be an ideal technology for smallholder rice farmers in Madagascar.

One early concern raised about the technique was that perhaps some of the extraordinary yield gains were simply coming from the fact that the farmers who adopted were *ex-ante* better, more productive farmers. There is some evidence for this. Barrett et al.(2004) found that about half of the observed productivity gains appeared to be due to farmer heterogeneity rather than the method itself. However, the technology nonetheless generated impressive average output gains of more than 84 percent.

Despite its obvious benefits and intensive extension efforts by an indigenous NGO in the mid to late 1990s, SRI had not taken off as expected. Adoption rates were generally low and the average rate of disadoption (the percentage of households who tried the method but later abandoned it) was around 40%, and those who adopted and retained the technique rarely put more than half of their rice land in SRI. Several explanations have been offered for the disappointing results. First, labor constraints at the household or village level might prevent farmers from adopting the technology. SRI requires additional labor input at a time of year when demands on farmers and workers are at their highest. A second and related explanation is that farmers might be unable to hire laborers

[2] SRI combines several techniques including: seeding on a dry bed, transplanting plants younger than 20 days old, spacing of at least 20 X 20 cm, frequent weedings, controlling the water level to allow aeration of the roots during the growth period of the plant.

or might need to work as day laborers themselves due to liquidity constraints. Because SRI is a low *external* input technology, it was initially believed that it would be widely accessible and affordable. However, the extra labor required does appear to be a significant obstacle. Poorer farmers might also fail to adopt the technology due to perceived or actual yield risk associated with the new method (presence of such a yield risk was confirmed by Barrett et al. 2004). Finally, low rates of adoption of SRI have sometimes been blamed on a perceived reluctance of Malagasy farmers to try new techniques.

The data used in the present study were collected in 2000. The original goal of the survey was to explain the relatively low rates of adoption and high rates of disadoption of SRI in the areas where it had been promoted in Madagascar. The five villages in the survey were purposively chosen based on access to SRI extension agents. Manandona and Anjazafotsy are villages in the central plateau near the city of Antsirabe in the province of Antananarivo. This area is well known for its productive and diverse agriculture that supplies the food processing industry and other markets around the country. Ambatovaky, Iambara and Torotosy are near the Ranomafana National Park in the Province of Fianarantsoa. These villages are in a more remote area and efforts to promote agricultural intensification reflect efforts to slow unsustainable deforestation associated with traditional, slash-and-burn rice cultivation (*tavy*).

Adopters and disadopters of SRI were oversampled to ensure sufficient numbers, but we are able to correct for this using sampling weights constructed from a census of farming households in each village. The data were collected in a single-visit survey of 317 households that included questions on household and farm characteristics, land holdings, SRI use, and problems with and perceptions of SRI. Using farmer recall and extension records, we have information on land holdings for farmers in the sample, SRI and off-season crop use for all farmers in the study sites and extension agent presence between 1994 and 1999.

Two previous papers (Moser and Barrett 2003, 2006) use these data to explore the adoption of SRI. Consistent with the technology adoption literature, these papers find evidence that farmer education, liquidity and labor availability matter. They also find that learning effects play an important role, not only in farmers' initial decisions to try a new technology, but also in the subsequent decisions as to what proportion of their cultivated area to put into the new method and whether or not to continue with the method in future years.

*Off-Season Crops*

In contrast to the heavily-promoted yet not widely-adopted SRI, another technology, off-season cropping (OSC), was widely adopted with almost no outside support in some of the same areas. Off-season crops are planted in the rice fields during the winter season; potatoes are the most common OSC in the areas surveyed. Off-season crops offer an interesting contrast to SRI because they require labor and purchased inputs (seed and fertilizer) after the rice harvest, when farmers typically have more time and money available. Furthermore, the OSC harvest comes at the beginning of the rice-growing season, when many farmers are short of both rice and cash. OSCs are seen by many farmers as a complement to rice intensification, since rotating crops and adding fertilizer (either organic or inorganic) generally improve soil fertility to the benefit of succeeding rice crops, and because the infusion of resources at OSC harvest facilitates the hiring of labor and frees the household from needing to work off-farm to earn wages to purchase food.

Unlike SRI, there was almost no disadoption of OSC. In Ambatovaky, where OSCs were introduced roughly at the same time as SRI, there was zero disadoption and approximately 84 percent of households practiced the method in 1999 (as opposed to only 26 percent practicing SRI). One reason might be that learning how to grow off-season crops appears to be much easier than learning SRI, which requires several simultaneous and significant changes to current rice cultivation practices. Seventy-two percent of all off-season crop adopters, and 60 percent of OSC adopters in Ambatovaky and Iambara, learned the method from other farmers, while only 30 percent of SRI adopters learned the technique this way. Analyzing the data collected on Off-Season Crops (OSCs) is somewhat complicated by regional differences. In the region of Antsirabe, OSCs have been grown for many years and adoption was already quite high at the beginning of the study period. In Torotosy, off-season cropping is not feasible for most farmers because there is too much standing water on the rice fields in the winter. There is also less of a need for it because they receive enough rain in the winter to grow winter crops in their upland fields.

*Descriptive statistics*

Table 1 presents the data on adoption of SRI and OSC by year. Adoption rates for SRI are actual population numbers taken from the sampling frame. OSC rates are from the survey data. SRI adoption peaks at 44 percent in Ambatovaky in 1998. Adoption appears to fall significantly in the villages where extension was no longer present in 1999, but also fell in Anjazafotsy from 19.4 percent in 1997 to 12.9 percent in 1999. Off-season cropping had been practiced in Manandona and Anjazafotsy for some years prior to the survey, as can be seen from the high rates of adoption at the beginning of the period. However, the method is adopted much more rapidly than SRI in Ambatovaky and Iambara, although adoption rates for both methods were similar in 1994. Figure 1 summarizes the adoption rates for the two methods across the five villages.

Table 1 also includes information on extension presence. The extension services were delivered by a Malagasy NGO promoting SRI. Thus these agents did not have a mandate to promote OSC. Two sites (Manandona and Anjazafotsy) had extension agents present over the entire period. Extension in Iambara and Torotosy did not begin until 1997. Due to funding problems, extension agents were not available in 1999 for three villages (Ambatovaky, Iambara and Torotosy). This gives us sufficient variation in extension availability across time and villages to study its effect.

Other data used in this study are presented in table 2. The data are summarized for all observations, OSC adopters and SRI adopters. Note that the latter two categories are not mutually exclusive. Adopters of both methods are slightly better educated than other farmers and are older, on average. There appears to be little difference in terms of the number of household members. Interestingly, there are more female-headed households adopting OSC than in the overall sample. Membership in a farmer organization is higher among SRI adopters. The variable “salaried work” is a dummy variable equal to one if a household member has a stable source of income, such as working for the government. This might provide needed liquidity to adopt new technologies. In the data, we do see a higher percentage of adopters with this source of income. Agricultural day labor refers to households relying on working for wages for other farmers. This is common among poorer farmers and farmers with little land of their own and is a reasonable proxy for lack of liquidity. Agricultural day laborers may also be labor constrained because they have less time to devote to their own fields. Far fewer SRI adopters rely on agricultural day labor for income.

Turning to farm and plot characteristics, we find that both adopters of OSC and SRI tend to have larger plots. Because both of these methods tend to be labor intensive, distance between a farmer’s different rice fields and the distance from the fields to the farmer’s home may be relevant factors in the adoption decision. There is relatively little difference in the percent of farmers reporting that their fields are prone to flooding (SRI adopters are slightly higher), but many fewer SRI adopters report that their fields are prone to drought. SRI requires careful control of water and the ability to let water in and out of the field as needed. Thus, farmers with drought-prone fields may either lack the necessary water control or are afraid that if they let water out of the field, they may not have water when needed later. Off-season cropping is practiced in the dry season and requires that enough moisture remain in the fields after the rice crop, but the crops cannot tolerate continuously flooded fields.

**4. Estimation results**

The objectives of this paper are to explain the different adoption patterns, explore the relationships between these two technologies and to evaluate the performance of hazard models applied to technology adoption. We present three separate models for SRI adoption. First, we present a hazard model that controls for unobserved heterogeneity. For comparison, we also include a fixed-effects regression model and a cross-sectional probit model. The dependent variable in the fixed-effects model is the proportion of land cultivated using the technology. The obvious disadvantage of this approach is the limited number of time-varying variables. In the probit model the dependent variable equals one if the farmer was using the method in the season prior to the survey. The probit estimation can be thought of as a somewhat naïve model in the sense that it is looking at who was using the method at the time of the survey and ignores the history of adoption. Marginal effects are reported for all models. Village fixed effects were included in models I and III and year dummies were included in model II, but these are omitted from the tables for brevity. Note that the interpretation of the signs of the coefficients in the hazard model differ from the other two models. A positive marginal effect should be interpreted as increasing the time to adoption (or reducing the likelihood of adoption in a given year) from the predicted median time of adoption of 6.5 years.

We begin by looking at the hazard model results for SRI in table 3. The presence of an extension agent reduces the time to adoption by roughly 3.7 years. Off-season crop use in the prior season also reduces the time to adoption, but by a smaller amount (1.8 years). However, this effect diminishes over time because the longer a farmer practices OSC, the less likely he/she is to adopt. Farmers with flood-prone fields are more likely to adopt SRI, while those with drought-prone fields are less likely. Being a member of a farmer organization, having salaried employment and larger plot size all speed adoption. While being an agricultural day labor reduces adoption. These results are consistent with previous findings (Moser and Barrett 2003, 2006). In particular, SRI appears to be more difficult for poorer, liquidity-constrained farmers to adopt.

The unobserved heterogeneity does not have a significant effect on SRI adoption. The test for this is the likelihood ratio test of θ, which in this case produces a chi-squared statistic of 0.49 and a p-value of 0.24. In other words, the observed variables sufficiently control for farmer characteristics in the case of SRI adoption. Adbulai and Huffman (2005) also find no evidence that unobserved heterogeneity has a significant effect on adoption in their application to cross-bred cows in Tanzania.

In the fixed-effects model (model II), extension reduces the proportion of land in SRI, a finding that contradicts model I. Similar to the hazard model, OSC use in the prior period encourages adoption. This model also includes experience with SRI. Not surprisingly, this has a positive effect on SRI use. There are few statistically significant variables in the probit model. Extension was dropped due to collinearity in the last period. OSC use has no effect.

Table 4 presents the off-season crop results. Extension presence slows or reduces adoption of off-season cropping. Because the primary job of these extension agents was the promotion of SRI, they may have convinced farmers to try SRI first. We find that SRI use speeds or increases adoption of OSC. Similar to the SRI results, plot size and having flood-prone fields speed adoption, but other farm and household characteristics have no significant effect. While plot size is related to wealth, the fact that salaried work and day labor have no effect suggests that liquidity is less of a constraint on OSC adoption than for SRI. Unlike SRI and many technologies studied in the literature, education does not have an effect on off-season crop use.

Interestingly, in the case of off-season cropping, unobserved heterogeneity does have a significant effect. The chi-squared statistic is 33.33, or a p-value of 0.00. For comparison, table 4 also includes the hazard models without the controls for unobserved heterogeneity. There are some noticeable differences in the magnitudes of the marginal effects. However, with the exception of membership in a farmer organization, which has a statistically significant effect in model II but not model I, the statistical significance and signs do not change between the models.

Model III (the fixed-effects model) also finds a negative effect of extension on OSC use. Both SRI use and experience have positive effects, as does experience with OSC. The probit model again has few statistically significant variables. Extension appears to increase the probability of OSC adoption. While the results of the fixed-effects models are largely consistent with those of the hazard models, we are obviously limited in our choice of variables. The probit models, while perhaps a bit simplistic for the purpose of exposition, demonstrate the limitations of the binary choice, cross-section approach.

Next, we turn to the question of disadoption of SRI, specifically addressing the question of whether off-season cropping reduces the incidence of disadoption. We present two models. A hazard model controlling for unobserved heterogeneity and a probit model in which the dependent variable equals one if the farmer adopted SRI and subsequently stopped using the method. Both models do find that years of OSC experience reduce the likelihood of disadoption. Besides the (omitted) village fixed-effects, this is the only statistically significant variable in the estimations. This is partly because the sample is reduced to those farmers who had tried SRI. Similar to the model of SRI adoption, there is no significant effect of unobserved heterogeneity.

## 5. Concluding remarks

Hazard models have rarely been used in published studies of technology adoption; yet they have several advantages. They can accommodate both fixed and time-varying variables and can control for unobserved heterogeneity. Therefore, they do not require panel data and only information on the timing of adoption is needed, but in doing so utilize more information than standard probit or logit models. In our application, the hazard models seem to perform well. Controlling for unobserved heterogeneity only matters in the case of off-season cropping, but has no significant effect in the case of SRI. Standard software packages now easily estimate these models, as well as the more readily understood marginal effects, and so we believe these models can improve the analysis of technology adoption issues in many cases.

In our application, we wanted to explore the relationship and contrast between two technologies, the System of Rice Intensification (SRI) and off-season cropping (OSC). The patterns of adoption in the areas of the study were quite different. Off-season crop adoption was wide-spread, where it could be practiced, while SRI had lower rates of adoption and high rates of disadoption. The technologies are practiced on the same fields, but at different times of the year. It was hypothesized that the extra revenue generated by one technology could provide the needed liquidity to adopt the other. We do find evidence to support this hypothesis for both technologies. Use in the prior season of one technology, increases the likelihood of adoption of the other. We find the same result in a fixed-effect regression model. In the case of disadoption SRI, years of off-season crop experience is associated with lower disadoption.

In terms of explaining the differences in adoption patterns, the evidence suggests that liquidity constraints are an impediment to adoption of SRI but not to the adoption of off-season crops. Farmers in a household with salaried employment are more likely to adopt SRI, while those relying on agricultural day wages for income are less likely. These variables have no significant effect on OSC adoption. Interestingly, better educated farmers are more likely to adopt SRI, while education has no effect on OSC. It seems likely that SRI, which requires several significant changes in rice cultivation practices in a single season, may be more complicated to learn and less educated farmers may not feel they are able to make these changes. These results suggest that overall, off-season cropping is more “adoptable” than SRI. In terms of the policy implications of this study, it seems clear that the best technologies sell themselves and letting farmers choose from a variety of options rather than pushing one particular technology is more likely to lead to success for the farmers.

Table 1. Adoption and extension presence by year

| Village | Year | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 |
|---|---|---|---|---|---|---|---|
| Manandona | SRI (% of households practicing) | 1.0 | 5.8 | 8.6 | 14.5 | 17.7 | 17.1 |
| | OSC (% of households practicing) | 50.6 | 55.4 | 65.1 | 75.9 | 80.7 | 86.7 |
| | Extension presence | yes | yes | yes | yes | yes | yes |
| Anjazafotsy | SRI (% of households practicing) | 2.4 | 7.3 | 11.3 | 19.4 | 16.9 | 12.9 |
| | OSC (% of households practicing) | 71.2 | 74.0 | 78.1 | 83.6 | 87.7 | 90.4 |
| | Extension presence | yes | yes | yes | yes | yes | yes |
| Ambatovaky | SRI (% of households practicing) | 4.8 | 10.3 | 16.7 | 28.6 | 44.4 | 26.2 |
| | OSC (% of households practicing) | 3.4 | 11.9 | 15.3 | 30.5 | 52.5 | 79.7 |
| | Extension presence | yes | yes | yes | yes | yes | no |
| Iambara | SRI (% of households practicing) | 3.7 | 5.6 | 5.6 | 11.1 | 12.0 | 7.4 |
| | OSC (% of households practicing) | 3.9 | 5.9 | 7.8 | 7.8 | 27.5 | 35.3 |
| | Extension presence | no | no | no | yes | yes | no |
| Torotosy | SRI (% of households practicing) | 1.3 | 5.3 | 8.0 | 18.7 | 18.7 | 0.0 |
| | OSC (% of households practicing) | 0.0 | 0.0 | 7.8 | 7.8 | 5.9 | 2.0 |
| | Extension presence | no | no | no | yes | yes | no |

Table 2. Descriptive statistics

| Household characteristics | All observations | | OSC | | SRI | |
|---|---|---|---|---|---|---|
| Observations[+] | 317 | | 216 | | 156 | |
| Farmer/household characteristics | mean | sd | mean | sd | mean | sd |
| Education (years) | 4.71 | 3.23 | 5.03 | 3.38 | 5.44 | 3.34 |
| Age (years) | 41.28 | 13.26 | 43.75 | 12.98 | 43.28 | 12.85 |
| Number of adults in households | 3.62 | 2.15 | 3.58 | 2.01 | 3.59 | 1.94 |
| Number of children in households | 3.19 | 2.29 | 3.16 | 2.40 | 3.13 | 2.19 |
| Female-headed household (%)[++] | 13 | | 17 | | 12 | |
| Member of farmer organization (%)[++] | 41 | | 39 | | 51 | |
| Salaried work (%)[++] | 16 | | 19 | | 24 | |
| Agricultural day labor (%)[++] | 22 | | 20 | | 13 | |
| Farm/plot characteristics | | | | | | |
| Total irrigated rice land (ares) | 59.28 | 63.31 | 65.93 | 72.07 | 71.74 | 80.91 |
| Distance between rice fields (minutes) | 18.44 | 17.41 | 18.39 | 16.31 | 16.11 | 13.63 |
| Distance to rice fields from home (minutes) | 19.81 | 26.78 | 21.52 | 28.77 | 20.49 | 24.49 |
| Fields prone to flooding (%)[++] | 15 | | 14 | | 17 | |
| Fields prone to drought (%)[++] | 39 | | 39 | | 30 | |

[+]note that OSC and SRI adoption are not mutually exclusive
[++] denotes a dummy variable

Table 3. System of Rice Intensification (marginal effects reported, standard errors in parentheses)

| | I] Hazard Model w/ controls for unobs. Hetero. | | II] Fixed effects model | | III] Probit model | |
|---|---|---|---|---|---|---|
| | dy/dx | | dy/dx | | dy/dx | |
| Extension presence | -3.670 | ** | -0.038 | ** | | |
| | (1.474) | | (0.014) | | | |
| OSC use prior season | -1.757 | ** | 0.036 | ** | 0.130 | |
| | (0.846) | | (0.014) | | (0.087) | |
| OSC experience (yrs) | 0.640 | ** | 0.001 | | 0.008 | |
| | (0.242) | | (0.005) | | (0.020) | |
| SRI experience | na | | 0.019 | ** | na | |
| | | | (0.006) | | | |
| Household/farmer characteristics | | | | | | |
| Education (years) | -0.151 | * | | | 0.010 | |
| | (0.088) | | | | (0.010) | |
| Age | 0.018 | | | | 0.001 | |
| | (0.021) | | | | (0.002) | |
| Number of adults in hh | 0.180 | | | | -0.009 | |
| | (0.138) | | | | (0.016) | |
| Number of children | 0.113 | | | | 0.005 | |
| | (0.117) | | | | (0.013) | |
| Female-headed hh | 0.151 | | | | -0.055 | |
| | (0.800) | | | | (0.078) | |
| Farmer organization | -1.695 | ** | | | 0.134 | * |
| | (0.560) | | | | (0.070) | |
| Salaried employment | -1.850 | ** | | | 0.194 | ** |
| | (0.565) | | | | (0.091) | |
| Agric. day laborer | 1.629 | * | | | -0.059 | |
| | (0.846) | | | | (0.074) | |
| Farm characteristics | | | | | | |
| Plot size | -0.014 | ** | 0.0002 | | 0.000 | |
| | (0.004) | | 0.0003 | | (0.000) | |
| Distance between fields | 0.034 | * | | | -0.004 | |
| | (0.021) | | | | (0.003) | |
| Distance to fields | -0.011 | | | | 0.002 | |
| | (0.012) | | | | (0.001) | |
| Flood-prone field | -1.188 | * | | | 0.030 | |
| | (0.638) | | | | (0.093) | |
| Drought-prone field | 1.664 | ** | | | -0.074 | |
| | (0.617) | | | | (0.061) | |
| observations | 1480 | | 1904 | | 317 | |
| Theta | 0.302 | | | | | |
| | (0.554) | | | | | |
| Likelihood-ratio test of theta=0: chibar2(01) | 0.49 | | | | | |

**(*) coefficients significant at the 5(10) percent level.

Table 4. Off-season cropping (marginal effects reported, standard errors in parentheses)

| Extension and technology use | I] Hazard Model w/ controls for unobs. hetero. dy/dx | | II] Hazard Model w/ no controls for unobs. hetero. dy/dx | | III] Fixed-effects model (dep.variable is proportion of area in technology) dy/dx | | IV] Probit model (dep. variable equals one if adopted) dy/dx | |
|---|---|---|---|---|---|---|---|---|
| Extension presence | 3.253 | ** | 3.272 | ** | -5.734 | ** | 0.924 | ** |
| | (1.278) | | (1.389) | | (0.780) | | (0.047) | |
| SRI use prior season | -3.780 | ** | -3.510 | ** | 1.939 | ** | 0.148 | |
| | (1.131) | | (1.188) | | (0.692) | | (0.118) | |
| SRI experience (yrs) | 0.752 | | 0.655 | | 2.453 | ** | 0.068 | |
| | (0.914) | | (0.840) | | (0.355) | | (0.043) | |
| OSC experience (yrs) | na | | na | | 0.434 | * | na | |
| | | | | | (0.268) | | | |
| Household /farmer characteristics | | | | | | | | |
| Education (years) | 0.027 | | 0.026 | | | | 0.000 | |
| | (0.116) | | (0.126) | | | | (0.013) | |
| Age | 0.039 | | 0.041 | | | | -0.005 | * |
| | (0.029) | | (0.032) | | | | (0.003) | |
| Number of adults in hh | -0.075 | | -0.072 | | | | 0.003 | |
| | (0.183) | | (0.211) | | | | (0.019) | |
| Number of children | -0.110 | | -0.082 | | | | 0.016 | |
| | (0.156) | | (0.178) | | | | (0.016) | |
| Female-headed hh | 0.149 | | 0.240 | | | | -0.004 | |
| | (0.958) | | (1.087) | | | | (0.112) | |
| Farmer organization | -1.044 | | -1.488 | * | | | -0.022 | |
| | (0.796) | | (0.893) | | | | (0.089) | |
| Salaried employment | -0.513 | | -0.499 | | | | 0.039 | |
| | (0.918) | | (1.023) | | | | (0.111) | |
| Agric. day laborer | 0.838 | | 0.555 | | | | 0.037 | |
| | (0.940) | | (1.018) | | | | (0.088) | |
| Farm characteristics | | | | | | | | |
| Plot size | -0.013 | ** | -0.014 | ** | 0.058 | ** | 0.001 | |
| | (0.005) | | (0.005) | | (0.017) | | (0.001) | |
| Distance between fields | 0.015 | | 0.015 | | | | 0.000 | |
| | (0.027) | | (0.030) | | | | (0.002) | |
| Distance to fields | -0.021 | | -0.025 | | | | 0.001 | |
| | (0.016) | | (0.018) | | | | (0.002) | |
| Flood-prone field | -1.753 | ** | -2.131 | ** | | | 0.099 | |
| | (0.876) | | (0.985) | | | | (0.100) | |
| Drought-prone field | 0.870 | | 1.384 | * | | | -0.083 | |
| | (0.728) | | (0.836) | | | | (0.080) | |
| observations | 1226 | | 1226 | | 1904 | | 317 | |
| theta | 2.982 | | na | | | | | |
| | (1.301) | | | | | | | |
| Likelihood-ratio test of theta=0: chibar2(01) | 33.33 | | | | | | | |

**(*) coefficients significant at the 5(10) percent level.

Table 5. Disadoption of SRI

| | I] Hazard Model w/ controls for unobs. Hetero. | | II] Probit model of disadoption (1 if household disadopted) | |
|---|---|---|---|---|
| Extension and technology use | dy/dx | | dy/dx | |
| Extension presence | -0.067 | | | |
| | (0.360) | | | |
| OSC use prior season | 0.434 | | -0.131 | |
| | (0.399) | | (0.157) | |
| OSC experience (yrs) | 0.187 | ** | -0.053 | ** |
| | (0.090) | | (0.030) | |
| Household /farmer characteristics | | | | |
| Education (years) | 0.042 | | -0.013 | |
| | (0.036) | | (0.015) | |
| Age | 0.013 | | -0.004 | |
| | (0.010) | | (0.004) | |
| Number of adults in hh | 0.014 | | -0.016 | |
| | (0.070) | | (0.027) | |
| Number of children | 0.033 | | -0.011 | |
| | (0.053) | | (0.021) | |
| Female-headed hh | 0.311 | | -0.015 | |
| | (0.372) | | (0.140) | |
| Farmer organization | -0.250 | | 0.093 | |
| | (0.239) | | (0.098) | |
| Salaried employment | 0.030 | | -0.055 | |
| | (0.287) | | (0.118) | |
| Agric. day laborer | -0.004 | | -0.059 | |
| | (0.336) | | (0.139) | |
| Farm characteristics | | | | |
| Plot size | 0.001 | | 0.000 | |
| | (0.002) | | (0.001) | |
| Distance between fields | 0.000 | | 0.000 | |
| | (0.009) | | (0.004) | |
| Distance to fields | 0.003 | | -0.002 | |
| | (0.006) | | (0.002) | |
| Flood-prone field | -0.069 | | 0.016 | |
| | (0.321) | | (0.129) | |
| Drought-prone field | 0.020 | | -0.037 | |
| | (0.239) | | (0.098) | |
| observations | 367 | | 156 | |
| theta | 2.98e-08 | | | |
| | (.0000388) | | | |
| Likelihood-ratio test of theta=0: chibar2(01) | 0.00 | | | |

**(*) coefficients significant at the 5(10) percent level.

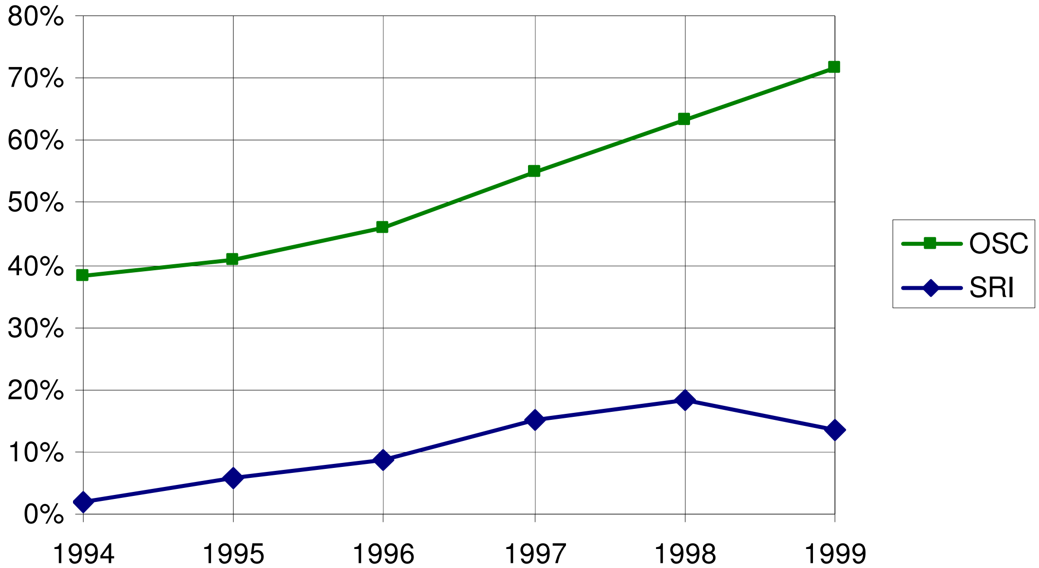


Figure 1. Percentage of households practicing off-season crop and System of Rice Intensification

**References**

Awudu Abdulai, Wallace Huffman (2005). The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. American Journal of Agricultural Economics, 87(3): 645–659

Christopher B. Barrett, Christine M. Moser, Joeli Barison, Oloro V. McHugh (2004). Better Technology, Better Plots or Better Farmers? Identifying Changes In Productivity And Risk Among Malagasy Rice Farmers. American Journal of Agricultural Economics, 86(4), 869–888.

William Broad (2008). Food Revolution That Starts With Rice. The New York Times, published June 17, 2008.

Jeffery Dorfman (1996). Modeling Multiple Adoption Decisions in a Joint Framework. American Journal of Agricultural Economics, 78:547–57.

Cheryl R. Doss (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. Agricultural Economics, 34 207–219.

Lire Ersado, Gregory Amacher, Jeffrey Alwang (2004). Productivity and Land Enhancing Technologies in Northern Ethiopia: Health, Public Investments, and Sequential Adoption. American Journal of Agricultural Economics, 86(2): 321-331.

Howard D. Leathers, Melinda Smale (1991). A Bayesian Approach to Explaining Sequential Adoption of Components of a Technological Package. American Journal of Agricultural Economics, 73(3): 734-742.

Christine Moser and Christopher Barrett (2006). The Complex Dynamics of Smallholder Technology Adoption: The Case of SRI in Madagascar. Agricultural Economics, 35(3): 373-388.

Christine Moser and Christopher Barrett (2003). The Disappointing Adoption Dynamics of a Yield-Increasing, Low External Input Technology: The Case of SRI in Madagascar. Agricultural Systems, 76: 1085-1100.

Hery Rakotomalala (1997). Comparison entre la Rizicullture Traditionnelle et le Systeme de Riziculture Intensive dans La Region de Ranomafana. Science Agronomique. Antananarivo, Universite d'Antananarivo.

M. Randrianasolo (1995). Contribution a l'Etude Comparative de Rentabilite de Differents Systemes Rizicoles: Cas du Fivondronana d'Arivonimamo. Agronomy. Antananarivo, Universite d'Antananarivo**:** 224.

Christopher Surridge (2004). Rice cultivation: Feast or famine? Nature 428, 360-361.