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Who benefits from climate-friendly agriculture? The marginal returns to a rainfed system of rice intensification in Tanzania ☆

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ABSTRACT

Agricultural production in sub-Saharan Africa faces a multitude of challenges arising from land degradation, climate change, and limited access to improved technology. In this context, technologies that raise farmers' crop productivity while mitigating risk exposure are particularly valuable. This study assesses the impacts of a modified, rainfed variant of the system of rice intensification (SRI) on expected yields, yield variance (variability) and yield skewness (exposure to downside risk) in Tanzania. The appeal of the technology lies in its yield-enhancing potential, its low demand for complementary external inputs as well as its drought resistance features. While the uptake of SRI has been considerable in Asia, the limited uptake in Africa is puzzling, particularly given its suitability for the African setting. Our empirical strategy relies on the estimation of marginal treatment effect (MTE) models. We find that, while the average effects on adopters suggest that SRI enhances yield and reduces the downside risk of crop failure, the marginal treatment effects indicate that only farmers with low resistance to adoption, benefit. Our analysis also highlights the importance of farmers' climate perception for the adoption of SRI and the need for policies that increase climate awareness to ensure food security. However, these results may well be specific to small scale, rainfed rice cultivation in Africa and therefore may not be generalizable to situations where SRI relies on irrigation.

1. Introduction

Farmers in much of the African continent endure persistently low productivity due to soil erosion, over-reliance on rainfall, and limited access to improved seeds and fertilizers, among other constraints. The growing literature on climate change predicts that Africa's agrarian economies are likely to disproportionately bear the burden of increased temperature and erratic precipitation through substantial agricultural yield losses (Dinar, Hassan, Mendelsohn, & Benhin, 2012; Solomon et al., 2007). Climate change is indeed likely to exacerbate the underlying risks associated with climate-dependent economic activities such as rainfed agriculture, which is likely to deter investment in the sector (Adger, Huq, Brown, Conway, & Hulme, 2003; Moser & Barrett, 2003). Adaptation strategies are essential in the mitigation of the likely adverse consequences of changing climatic conditions. In this context, technologies that raise farmers' crop productivity while mitigating risk exposure are particularly valuable. However, many conventional technologies, such as improved crop varieties, often result in greater crop yield, but at the expense of increased yield variability. This study assesses the impact of a counterintuitive technology, the system of rice intensification (SRI), in Tanzania, on expected yield, yield variability and exposure to downside risk of crop failure, captured by the variance and skewness, respectively.

The system of rice intensification was developed in the 1980s in Madagascar as a set of alternative management practices to help

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poor farmers—who were typically excluded from the input-intensive Green Revolution—increase their yields, while using cheap organic inputs and less water. Because African farmers have limited access to water resources (due to insufficient rainfall and a lack of access to irrigation technologies), costly improved seeds, and inorganic fertilizers, SRI presents an opportunity for them to achieve higher yields, making it a suitable climate change adaptation strategy (Thakur & Uphoff, 2017; Thakur, Uphoff, & Stoop, 2016; Adhikari, Sen, & Uphoff, 2010). SRI is based on four principles that rely on a counterintuitive set of agronomic practices. Although the exact set of practices are intended to be modified to suit the application setting and therefore vary in different settings, the guiding principles are: (1) early transplanting (eight to 15 days old) of carefully managed seedlings; (2) single, widely spaced transplants to allow early and regular mechanized weeding; (3) careful and controlled water management; and (4) application of compost to the extent possible (De Laulani, 1993a; De Laulani, 1993b; Stoop, Uphoff, & Kassam, 2002; Noltze, M, Schwarze, & Qaim, 2013). Unlike conventional paddy rice cultivation, SRI does not rely on flooding, but rather on moist soil, with intermittent irrigations (Stoop et al., 2002), which is particularly well suited to regions where water is a limiting factor.

This study is relevant to the African context for three reasons. First, because climate change is having a devastating effect on the African continent, climate-adaptive practices such as SRI are essential. Second, resource-constrained African agriculture requires innovations that are more attuned to its traditionally low external input technologies. Third, while much of the developing world has experienced a green revolution of some sort, these conventional approaches have failed in Africa, which means its farmers must seek answers in flexible and locally adaptable technologies such as SRI. Over the past two decades, a growing body of research has found that SRI is able to deliver substantially higher yields than the conventional paddy method (Uphoff et al., 2002; Barrett, Moser, McHugh, & Barison, 2004; Uphoff, 2007; Noltze et al., 2013; Alem, Eggert, & Ruhinduka, 2015; Thakur & Uphoff, 2017), while generally reducing input requirements—fewer seeds, less water and inorganic fertilizers (Wu, Ma, & Uphoff, 2015; Adhikari et al., 2010). Besides, SRI is reported to produce more robust and resilient crops in the face of extreme weather events, pests, and disease (Stoop et al., 2002; Noltze et al., 2013; Thakur & Uphoff, 2017). It has also the capacity to reduce greenhouse gas emissions in rice cultivation. In addition to fostering food security and adaptation, SRI mitigates against climate change, and hence qualifies as a climate-smart agricultural practice (Thakur & Uphoff, 2017; Thakur et al., 2016). As a result, over the past two decades, SRI has diffused in the paddy rice growing regions of Asia (e.g., China, India, Vietnam) as well as in parts of Africa (e.g., Tanzania, Mali).[1]

However, critics—primarily from the scientific agricultural community—have challenged the validity of the findings that SRI provides greater yields and reduced risk of failure. For instance, Sheehy et al. (2004) contend that the claim that SRI improves yields relative to conventional irrigation methods is based on studies that likely suffer from measurement errors, especially in light of the large differences between predictions from agronomic models and reported yields from SRI sites. Examining 40 SRI sites in Madagascar and Asia, McDonald, Hobbs, and Riha (2006) find no evidence of a systematic or even occasional yield advantage of SRI compared to conventional best management practices (BMP) outside of Madagascar. Furthermore, Dobermann (2004) argues that, despite reduced water requirements, intermittent irrigation places the crops at a higher risk of failure. Finally, although SRI economizes on certain inputs, its labor intensity has in the past been argued to be a limiting factor for extending cultivation beyond marginal land areas (Dobermann, 2004; Tsujimoto, Horie, Randriamihary, Shiraiwa, & Homma, 2009). However, in recent years, the adoption of new techniques such as direct seeding rather than transplanting, and the use of herbicides to reduce the need for hand and mechanical weeding, have been shown to significantly reduce labor requirements (Thakur & Uphoff, 2017; Wu et al., 2015).

Despite these early debates, SRI is generally accepted as a practice that can help poor and vulnerable farmers increase their yields, while making them resilient to the vagaries of unfavorable weather, especially in Africa.[2] Therefore, the slow diffusion of SRI resulting from the slow adoption rate and high rate of disadoption among poor farmers is all the more puzzling (Stoop et al., 2002; Moser & Barrett, 2003; Moser & Barrett, 2006; Takahashi & Barrett, 2013). Why would resource-poor rice growers in Africa not adopt a method that can help relax the binding constraints they face under the conventional paddy method? Various explanations have been offered. Moser and Barrett (2003) and Moser and Barrett (2006) attribute the slow adoption and non-trivial disadoption rates to the large hidden opportunity costs of engaging in SRI. SRI is initially labor-intensive, particularly early in the season when labor demand for field preparation, setting up a nursery, transplanting, weeding, mulching and composting is high. During this phase, credit constrained farmers are most at risk because they cannot afford the required reallocation of paid off-farm labor into unpaid family farm labor, or hire labor to perform SRI's time-consuming set-up activities. These farmers are therefore unable to reap the potential productivity gains from SRI (Barrett et al., 2004). Abdulai and Huffman (2014) echo a similar argument in their analysis of low adoption rates of soil and water conservation technologies in rice growing regions of Ghana.

However, there is evidence that, as farmers learn the new techniques, labor demand diminishes to such an extent that SRI becomes labor-saving (Uphoff, 2006; Barrett et al., 2004) For instance, in Madagascar, Barrett et al. (2004) find that labor intensity decreases by 4.2% and 10.9% by year 4 and year 5 of SRI practice, respectively. Similarly, Gathorne-Hardy, Reddy, Venkatanarayana, and Harriss-White (2016) show that, in India, the overall demand for labor is reduced significantly under SRI, due to an increase in labor productivity by a factor of 2.4 (compared to the control group) resulting from the reduction in labor requirement during transplanting.[3] Furthermore, since SRI constitutes a set of counterintuitive and unfamiliar agronomic practices, success relies heavily on sustained training and extension services. When these services are unavailable, or not sustained over time, farmers may have little incentive to adopt SRI (Dobermann, 2004). For instance, in both Timbuktu, Mali and Sichuan, China, the continued presence of SRI expertise played a significant role in SRI diffusion (Styger et al., 2011; Li et al., 2005).

Yet another explanation for slow adoption is that adopting SRI may have impacts beyond the mere expected yields. If SRI were to impact yield variability, or increase the risk of crop failure as argued by Dobermann (2004), then these impacts could also help

[1] As of 2020, SRI has been validated in no less than 61 countries around the world, including 23 African countries, such as Mali, Nigeria, Tanzania, and Kenya (See http://sri.ciifad.cornell.edu/countries/index.html. Accessed 23 June 2020).

[2] Styger, Aboubacrine, Attaher, and Uphoff (2011) show that, in Timbuktu, Mali, the adoption rate of SRI grew manifold within three years. They attribute this growth to availability of finance to support interested farmers, a change in the mindset of farmers and extension workers on SRI, and improved yield—which more than doubled after adoption. However, unlike in Asia where the diffusion of SRI has accelerated, uptake has remained marginal in Africa.

[3] By the same token, Tech (2004) shows that after three years of SRI practice, 55 percent of Cambodian farmers considered the practice easier due to its reduction in labor requirements. Further, in China, Li, Xu, and He (2005) find that 100 percent of SRI farmers regarded labor saving as SRI's greatest benefit followed by mulching/no weeding (54.5 percent) and water saving at (45.5 percent).

explain this puzzle. We are therefore concerned with establishing the relationship between SRI adoption and the first three central moments of rice yield. Farmers with inferior SRI yields would arguably disadopt SRI. By the same token, farmers who are averse to increased yield variability (risk averse) or averse to increased exposure to downside risk could potentially shy away from SRI even if it were to deliver higher yields.

This study relates to Anthofer (2004) who conducts a risk analysis of a farmer's choice between conventional rice practices and SRI, when the latter bears additional risk of adverse climatic conditions. His findings indicate that the downside risk of switching from the conventional practice to SRI is only 15 percent. However, our approach is different from Anthofer's (2004) in three major ways. First, our analysis focuses on two separate measures of risk exposure (yield variance and skewness) as opposed to Anthofer's single measure of downside risk, which allows us to capture a richer set of farmers' risk behavior. Second, our two measures of risk exposure are derived from the estimation of individual production frontiers, while Anthofer's (2004) is based on arbitrarily set upper-bound yield. Third, the moments approach enables us to control for farmer and physical farm characteristics, whereas Anthofer's (2004) study does not factor in such individual differences as predictors of yield. Namara, Weligamage, and Barker (2003) is another related study. Based on Sri Lankan data, it assesses the impact of risk and uncertainty on SRI adoption decisions, as influenced by the availability and distribution of rainfall. Using logistic regression, the study investigates the impact of the observed production risk differential between rainfed and irrigated farming systems on SRI adoption probability between farmers situated in different locations. Their analysis shows that the probability of adoption of SRI is lower for irrigated farms than for rainfed farms.

Our study makes three distinct contributions to the literature. First, we suggest that the pattern of the first three central moments of rice yield may provide some avenue to understanding the puzzlingly low adoption rate of SRI in Africa. This is in contrast to Asia, where 90 percent of the world's rice is grown and the adoption of SRI is considerable.[4] We extend the limited literature on the role of risk exposure in technology adoption by focusing on the system of rice intensification, an integrated technology designed to reduce production risks. By doing so, we move away from a narrowly focused analysis of productivity impacts. For this purpose, we use a moment-based approach that characterizes the stochastic nature of the technology (Kim & Chavas, 2003; Di Falco & Chavas, 2009).

Second, we introduce a novel empirical model to the technology adoption literature to demonstrate why it is the adopters' distribution of benefits rather than their mean benefits (on which the literature has focused) that matters most in accounting for SRI low adoption rates in the African setting. Although recent empirical studies use endogenous switching regression (ESR) models to show that SRI brings substantial benefits to the average adopter (Noltze et al., 2013; Alem et al., 2015), how these benefits are distributed, given the presence of significant observed and unobserved heterogeneity, is missing if we are to account for farmers' technology adoption choice. Thus, we need to know the treatment effects for the farmer at the margin of indifference between adopting or not adopting SRI rather than the average farmer's treatment effects. This is, in essence, the purpose of the marginal treatment effect (MTE) framework developed by Heckman and Vytlacil (2005). Accordingly, our empirical strategy relies on the estimation of the marginal treatment effect (MTE) of SRI adoption. Although this framework has gained traction in the labor and education economics literature lately, we are not aware of any studies in the agricultural technology adoption literature that uses this methodology to understand how farmers' heterogeneity, both observed and unobserved, influences their treatment effects at the margin, which is critical for any successful policy design.

Third, our analysis sheds light on the role of perception of climate change as a key factor that influences farmers' adaptation strategies. We build on Maddison (2007) and Bryan, Deressa, Gbetibouo, and Ringler (2009) analysis of climate change perceptions and its impact on farm level decision making. These are two related studies that assess the ability of farmers in Africa to detect climate change, and attempt to ascertain how farmers adapt as a result of their perception of climate change. Their findings show that farmers behavioral responses to perceived climate change tend to be related more to recent climate events or trends than to long-term changes in average conditions (Smit, Burton, Klein, & Wandel, 2000; Thomas, Twyman, Osbahr, & Hewitson, 2007; Bryan et al., 2009). Our analysis demonstrates the significance of accounting for perception of climate change in adopting technologies such as SRI which have important climate adaptation features. It should be noted, however, that it is not the responsiveness of SRI adoption to climate change per se that we analyze here, but rather the behavioral response resulting from climate change perception. This is because farmers' ability to perceive effects of climate change is a precondition for their decision to adapt. For this reason, we are using basic perception measures which, although imperfect and require improving, are widely used in the current literature.[5]

We find that farmers who perceive occurrences of climatic changes are more likely to adopt SRI because of the climate resilient features of the technology. Importantly, our results also reveal that the effects of SRI adoption vary considerably both in magnitude and sign, and are contingent on individual farmers' resistance (or conversely, inclination) to adopt SRI, which reflects their unobserved characteristics.[6] In particular, we find that SRI adoption enhances yield (a finding that is in line with numerous SRI evaluation studies), and increases yield variability while reducing exposure to downside risk of crop failure (a novel finding in the SRI evaluation literature) for farmers with low resistance to adoption. By contrast, farmers who display a high degree of resistance to SRI adoption experience lower yields, lower variability risk and increased downside risk of crop failure.

These findings suggest that SRI adoption might be constrained not by a lack of yield-enhancing and downside risk-reducing benefits, as is shown in this paper, but by failures to raise sufficient awareness about the technology. Thus an institutional response that provides information on the merits of SRI could prove invaluable in shaping farmers' perception of the technology and consequently encourage technology adoption. In line with this, Uphoff (2006) argues that effective SRI adoption (and reduced disadoption) requires innovative outreach practices that involve productive cooperation among farmers, researchers, extensionists, government agencies, and the private sector, instead of the one-way technology development-extension approach. In this regard,

[4] We thank an anonymous reviewer for suggesting two alternative explanations that are not considered in this study. First, the amounts of resources expended for disseminating and supporting SRI in Africa have been marginal compared to Asia (particularly in India, China and Vietnam). A second major difference is that rice production is typically labor-intensive in most of Asia, so that the labor-saving potential of SRI may emerge quickly. On the other hand, in most of Africa, rice production (and agriculture in general) is labor-extensive, so any start-up with SRI is likely to raise labor requirements relatively more than existing practice.

[5] Several studies point to bias in the perception of climate change associated with different factors. In line with this, Howe and Leiserowitz (2013) find that the subjective experience of local climate change is dependent not only on external climate conditions, but also on individual beliefs, with perceptions apparently biased by prior beliefs about global warming. In addition, Weber (2010) argues that recent events are likely to be given more weight than distant events in the evaluation of risky options.

[6] This point will be made clearer in Sections 4 and 5.

extension services have a critical role to play in promoting the technology. Given the importance of climate information to the adoption of SRI, these services can also be combined with information technology to enable farmers to access useful weather and climate information. This can be done at fairly low cost given the penetration of mobile devices even in the poorest communities. Such an intervention has the potential to contribute to food security.

The rest of the paper is organized as follows: In Section 2, we present background on SRI adoption and climate change in Tanzania. The survey strategy and data are discussed in Section 3, while the estimation methodology is provided in Section 4. Section 5 presents the empirical findings and Section 6 concludes the paper.

2. Background: Climate change and SRI adoption in Tanzania

Vulnerability of rainfed agriculture to climate change could have far-reaching consequences for the welfare of smallholder farmers due to reduced agricultural yields. Recent findings in Tanzania suggest that climate change may lead to shorter growing seasons and stress on cash crops due to increased moisture, heat, and pests (Mongi, Majule, & Lyimo, 2010), exacerbating food insecurity (Arndt, Farmer, Strzepek, & Thurlow, 2011). Tanzanian semi-arid agriculture is characterized by inadequate soil moisture which is further exacerbated by a changing climate evident in prolonged droughts, a reduction in overall amounts of annual/seasonal rainfall, inadequate and uneven distribution of rainfall, and unpredictable onset and length of the rainy seasons (Kangalawe & Lyimo, 2013). Ahmed, Diffenbaugh, Hertel, and Martin (2012) find that changes in climatic conditions affect yield variability and that high yield variability of staple grains is associated with large increases in poverty. However, based on economy-wide effects of climate change in Tanzania, Bezabih, Chambwera, and Stage (2011) contend that, despite the projected reduction in agricultural productivity, the negative impacts could be fairly limited if policies are introduced that enable farmers to respond appropriately to climate change.

Policies promoting adoption of technologies that allow farmers to adapt to climate change and climate variability are of particular interest in this regard. However, in addition to their costliness, conventional yield-enhancing technologies (e.g., improved crop varieties, cultivation of paddy rice) may be unsuitable for poor and vulnerable farmers particularly where they lead to a rise in yield variability and to greater exposure to downside risk (Kim & Chavas, 2003). For instance, in Tanzania, the conventional flooding techniques in paddy fields are deemed inefficient, given limited water availability and growing seasonal variability (Katambara et al., 2013a). The introduction of SRI in 2006 aimed to lessen the water intensity of rice production, improve yields, and consequently increase farmers' incomes. Crops cultivated under SRI are also reported to be more resilient in the face of extreme weather events, pests, and diseases.[7]

A simplified, rainfed variant of the SRI developed in Madagascar was introduced in several regions of Tanzania in 2006. It entails shallow planting of 1–2 cm of transplanted seedlings aged 8 to 12 days on a square grid of 20–25 cm, fertilizer application and weeding (Nakano, Tanaka, & Otsuka, 2018; Katambara et al., 2013b). This variant of SRI has met some success with regard to yield improvement and increased profitability. Nakano et al. (2018) find that farmers who adopted this modified, rainfed SRI (dubbed MSRI) achieve on average a yield of 4.7 tonnes per hectare as opposed to 2.9 tonnes per hectare for non-adopters. On irrigated land, the adoption of SRI has been associated with water efficiency (up to 64% improvement) and increased yields from 3.8 tonnes per hectare (with conventional methods) to 6.3 tonnes per hectare (Katambara et al., 2013a). Despite these seemingly promising results, adoption of SRI has been limited in Tanzania (Katambara et al., 2013a). In the following sections, we investigate the determinants of SRI adoption among rainfed farmers (with no access to irrigation) in the Morogoro region of Tanzania, as well as the effect of adoption on the first three central moments (mean, variance, and skewness) of rice yield.[8]

3. Data

The data used for the empirical analysis is based on a survey conducted in the Kilombero district of Morogoro region, one of the largest rice producing regions in Tanzania. In this district, 334 rice farming households were randomly selected from eight villages in the farming season ending in June, 2013. The survey collected detailed data on socio-economic household characteristics, as well as information on farming inputs (from plot preparation to the post-harvest) and outputs, plot-specific information, and marketing information. Unlike the standard SRI package of practices applied in irrigated farms in other parts of the world, the variant of SRI introduced among rain-dependent farmers in Kilombero, Tanzania, necessitated a number of modifications to fit local agro-ecological conditions. For example, because none of the sampled farmers had access to irrigation facilities on any of their plots,[9] an intermittent irrigation component of standard SRI was not part of the package, limiting the possibility to assess the water saving advantage of the technology. The SRI package in this setting consisted of the following components: (1) sorting of the rice seeds to select good versus bad seeds prior to planting; (2) square grid planting in a 25 cm $\times$ 25 cm grid square pattern of 1–2 seed (lings) per hole; (3) mechanical weeding using simple hand-held mechanical weeders; (4) use of chemical fertilizer[10]; and (5) use of Saro 5, a popular improved seed variety in Tanzania. We consider a household to be SRI if it adopts at least four of these five components.[11] None of these components is applied universally by all adopting households, which underscores the observation that SRI adoption is partial.[12]

[7] There is considerable literature that discusses the climate-resilient nature of SRI in Africa. A recent FAO report (2014) highlights the importance of SRI in addressing constraints associated with water shortages caused by environmental degradation and disturbance of waterways, which has typically resulted in crop failure and low yields. The role of SRI as an effective climate change adaptation strategy in the African setting is also highlighted by Aune, Nagothu, Kjell, and Mehreteab (2014). The study shows that although SRI is found on a very limited scale in Tanzania, in moisture-stressed settings, it has often contributed to substantial (up to twofold) increase in yield.

[8] It should be noted, however, that the adoption of SRI has increased significantly in recent years (FAO, 2014). SRI was introduced in the Morogoro region by Kilombero Plantations Limited (KPL) with significant funding from international development partners. However, Mittal, Mousseau, Tajdin, Farrell-Bryan, and Young (2015) report three major issues which might have impacted SRI adoption rates unfavorably. First, KPL's land acquisition and insufficient compensation resulted in adverse impacts on farmers' livelihoods. Second, the SRI outgrower contract between KPL and local farmers left many farmers heavily indebted. Third, the variant of SRI that was introduced relied heavily on external inputs (e.g., the use of inorganic fertilizers and Saro 5 seeds), which is reportedly at odds with the needs of many farmers.

[9] This is consistent with national averages where less than 1 percent of irrigable agricultural land is under irrigation (i.e. only 289,245 ha out of 29.4 million ha nationwide), the majority of which is owned by commercial farming companies (United Republic of Tanzania, 2009).

[10] According to Thakur and Uphoff (2017), more organic matter in soil supports larger, more diverse, more active populations. In this respect, Uphoff (2012) recommends that, whenever possible, organic fertilization should be preferred to inorganic fertilization, which is not required to obtain higher yields. The argument being that, because the former supports the soil biota better, it does more to improve the soil's structure and functioning than the latter.

[11] We therefore do not control for these characteristics in our estimations.

[12] Each of the components is applied on almost 90 percent of the adopting plots. This is comparable to related studies (e.g. Noltze et al., 2013; Takahashi & Barrett, 2013).

The allocation of plots for SRI occurred as follows: Initially, farmers gave information on all their rice-planted plots in the survey year, by SRI status. It was noted that multiple plot cultivation was only common with traditionally-farmed rice varieties but not with SRI. Whenever a household adopted SRI the method was applied in one plot only. For the non-SRI plots, a representative plot was selected using a simple random technique in order to minimize plot-level selection bias. In Section 4, we discuss the econometric steps we take to further control for potential selection bias resulting from systematic selection of plots into SRI and non-SRI categories.

We report the summary statistics resulting from the estimation sample in Table 1. The table presents the mean of the variables used in the estimations by SRI adoption status, as well as the mean difference between the adopter and non-adopter groups. With an adoption rate of approximately 58 percent, a total of 178 households in the estimation sample adopted SRI on one of their plots during the previous agricultural season. On average, households adopting SRI tend to be larger and headed by older farmers (44.8 versus 40.5 years for non-adopters). They are typically wealthier, have more experience in rice farming, and have a denser social network. They also tend to receive considerably more visits from extension services. These differences are statistically significant at least at the 5 percent level. However, we do not find any statistically significant difference in education level across the two groups.

Farmers in our sample typically practice SRI on smaller plots (1 acre compared to 2.9 acres) that are located closer to their homesteads (3.7 km vs. 4.8 km), a likely indication of the need to frequently attend to the plots. On average, these plots are more fertile than the conventionally cultivated plots.[13] However, we do not find any significant difference across plots with regard to either their fertility or their slope. Consistent with previous literature on SRI, we find that practicing SRI initially requires considerably more labor and considerably fewer seeds. On average, a SRI plot requires 65% more labor but 43% fewer seeds than non-SRI plots (56 man-days vs. 34 man-days, and 34 vs. 56 kg, respectively). The key dependent variables, in addition to SRI adoption, are yield, the variance, and the skewness of the yield. Yield is calculated as the log of total rice harvest per acre of cultivated land in tonnes. Preliminary assessments suggest that SRI farmers obtain significantly more yield but experience greater yield variance and skewness than their counterparts.

We report below the distributions of rice yield by SRI adoption groups. Fig. 1 shows that, on average, adopters experience higher yields than non-adopters. However, the yield distribution for adopters exhibits a greater variance while being more skewed to the right than the yield distribution for non-adopters. Thus, the first three central moments of the rice yield indicate that SRI adopters are more productive and less exposed to downside risk or probability of crop failure, but face greater yield instability than non-adopters. Critically, the right tail of the distribution for SRI adopters is extremely thin, suggesting that the density allocates little probability mass to five observations with unusually high yields. Those five observations appear to be outliers as their squared residuals are extremely high following an analysis of the leverage versus the squared residuals. If we were to exclude the five outliers, then the skewness of the distribution for SRI adopters would turn negative, suggesting crop failure. The Kolmogorov–Smirnov test suggests that two distribution functions are significantly different at the 1% level with a p-value of 0.000.

Table 1
Summary Statistics.

Variables	Sub-samples		
	Mean Adopters ($N = 178$)	Mean Non-Adopters ($N = 127$)	Mean Difference
Household Characteristics			
Household size	4.950	4.380	0.57***
Age of household head	44.80	40.50	4.31***
Education of household head (years)	7.040	7.020	0.020
Rice farming experience of head (years)	16.08	13.86	2.23**
Wealth (Tanzanian Shillings)	412503.51	247706.54	164796.98***
Production Inputs			
Total labor supply (man days)	56.40	34.28	22.12***
Seed rate usage (kg/acre)	14.05	24.73	−10.68***
Plot Characteristics			
Plot size (acre)	1.010	2.920	−1.91***
Very fertile (Yes = 1)	0.400	0.400	0
Gently sloping plot (Yes = 1)	0.120	0.130	−0.020
Plot distance (km)	3.660	4.750	−1.09**
Distance to market (minutes)	107.0	67.35	39.64
Adaptation Strategy			
Change of crops: Yes	0.540	0.440	0.10*
No	0.440	0.530	−0.090
Unsure	0.020	0.030	−0.010
Social & Professional Interactions			
Social connections	0.940	0.770	0.17***
Extension frequency visits	1.400	0.230	1.18***
Instrument			
Perception of Rain decrease	0.600	0.540	0.060
Outcome Variables			
Yield (tonne per acre)	2.945	1.994	0.951***
Variance Yield	0.240	0.120	0.12**
Skewness Yield	0.200	−0.050	0.25*

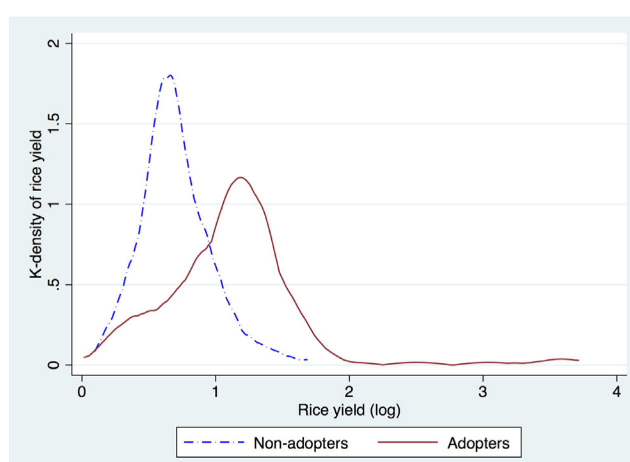

Fig. 1. Distributions of Yield by Adoption Group.

[13] The plot fertility variable was constructed from a self-reported response given by the farmer when asked to rank a given plot's soil fertility on a range of 1 = very fertile; 2 = fertile and 3 = not fertile. We then constructed a "very fertile" dummy that assigns a value equal 1 if the response was "very fertile" and 0 otherwise.

Finally, households were also asked about their perceptions regarding changing climatic patterns over the past 10 years. Perception about climate change is captured by a binary variable that indicates whether a farmer has perceived a pattern of declining rainfalls over the past decade. This dummy variable is constructed based on farmers' direct response to the question "Have you noticed any changes in the average rainfall over the last 10 years?". Nearly 60% of SRI adopters reported having observed a decrease in the average rainfall, as opposed to 54% of the non-adopters, although the difference is not statistically significant. Our variable is similar to the one introduced by Maddison (2007) on perception of, and adaptation to climate change. Consistent with the evidence that local knowledge, and personal experience of extreme events are critical in shaping beliefs about climate change (Roncoli, Ingram, & Kirshen, 2002; Vogel & Brien, 2006; Thomas et al., 2007), we allow our climate change perception variable to depend on individual farmers' village of residence. The Pearson Chi-square test indeed suggests a strong rejection of the null hypothesis that climate change perception is independent of village of residence, at the 1% level. This implies that the adoption decision should incorporate the interaction between climate change perception and village of residence as a set of explanatory variables.

It is important to note that, due to the problem of self-selection (or endogeneity bias) we cannot attribute all the differences presented in Table 1 to SRI adoption. Given that SRI farmers are more socially connected, receive more extension services, and apply the technology on smaller plots, adopters and non-adopters could still have outcome differences even without technology adoption.

4. Conceptual framework and econometric methodology

4.1. Motivation

Our analysis is based on the premise that farmers will embrace yield-enhancing technologies such as SRI if they expect increased welfare from the gains of higher yields. To the extent that SRI is conceived and perceived as a risk mitigating practice, it is expected to bring additional welfare benefits to poor and risk-averse farmers, whose welfare may be adversely affected by mean-preserving increases in the variance of yield and in the associated cost of risk exposure measured by skewness (e.g. the probability of crop failure). Our analytical framework relies on a moment-based specification of a farmer's stochastic production function (Antle, 1983; Di Falco & Chavas, 2009).

Since increased variance does not distinguish between unexpectedly good and bad events, and given that avoidance of crop failure is a major objective of farmers in sub-Saharan Africa (Di Falco & Chavas, 2009), incorporating the notion of skewness in measuring the cost of risk exposure is critical. While risk averse farmers may have an incentive to reduce the variance of returns, farmers exhibiting aversion to downside risk have an incentive to grow varieties that positively affect the skewness of the distribution of returns, thus reducing their exposure to downside risk (e.g. severe drought leading to crop failure) (Kim & Chavas, 2003; Di Falco & Chavas, 2009). Thus, a moment-based approach is able to provide insight into the extent of risk exposure.

Following Di Falco and Chavas (2009), we model a farmer's stochastic production function as $y = g(X, \upsilon)$, where g is a continuous and twice differentiable function, X is a vector of factors of production (e.g., inputs, assets, farmer and farm characteristics) and υ is a vector of random variables that captures production risk. In this framework, exposure to risk is captured by the higher moments of $g(X, \upsilon)$, which are determined following the econometric estimation of the production function:

$$g(X, \upsilon) = f_1(X, \beta_1) + \eta$$

where $\mathbb{E}[g(X, \upsilon)|X] \equiv f_1(X, \beta_1)$ is the mean or first central moment of $g(X, \upsilon)$ and $\mathbb{E}[\eta|X] = 0$. The second (variance) and third (skewness) central moments of $g(x, \upsilon)$ are estimated by:

$$\mathbb{E}\left\{[g(X, \upsilon) - f_1(X, \beta_1)]^k|X\right\} = f_k(X, \beta_k), \quad \text{for } k = 2, 3$$

We are concerned with estimating the effects of the set of covariates X on the mean, variance, and skewness of output. While the mean output is expected to be strictly increasing and concave in the factors of production, the effects on the variance and the skewness of output remain an empirical question. This is because a particular factor of production X_m could either increase $(\partial f_k/\partial X_m > 0)$, decrease $(\partial f_k/\partial X_m < 0)$ or have no effect $(\partial f_k/\partial X_m = 0)$ on variance or skewness (Di Falco & Chavas, 2009; Simtowe, Amondo, Marenya, Sonder, & Erenstein, 2019). Increased variance reflects enhanced output variability and therefore greater production risk due to the spreading of output from the center to the tails of a distribution. An increase in skewness on the other hand, indicates a reduction in downside risk because it involves a smaller probability of low output. In other words, reducing downside risk implies decreasing the asymmetry of the risk distribution toward high output, holding both mean and variance constant (Menezes et al., 1980; Di Falco & Chavas, 2009).

Using this production function framework, we estimate the impact of the new technology (SRI) on outcome variables between adopters and non-adopters beyond the usual mean difference by assessing its impact on higher central moments of rice yield, namely, variance and skewness. However, given a farmer's selection into SRI, adoption is unlikely to be random. Therefore estimating the effects of adoption using ordinary least squares (OLS), which assumes random selection, is potentially biased. Overall, to examine both the determinants of adoption of new technologies or agricultural practices, and the expected effect of such treatment, recent studies in the agricultural and development economics literature have applied endogenous switching regression models (Alem et al., 2015; Noltze et al., 2013; Abdulai & Huffman, 2014).

These models facilitate the estimation of the average treatment effect on both the treated (ATT) and the untreated (ATU) households. These effects are typically constant, which tells us little about how they are distributed across individuals, given the presence of unobserved heterogeneity. The aggregate parameters therefore could potentially conceal considerable variation in individual outcomes. In fact, given unobserved characteristics, the expected treatment effects could be so low for some farmers that they provide little to no incentive to adopt the new technology. Therefore, identifying who gains most from treatment, based on their observed and unobserved characteristics, is crucial for understanding who selects into treatment and who does not. This requires the estimation of the marginal treatment effect (MTE), defined as the expected treatment effect given observed covariates and a latent variable representing unobserved, individual-specific resistance to treatment. The concept of marginal treatment effect was introduced by Bjrklund and Moffitt (1987), and generalized by Heckman and Vytlacil (2005), Heckman and Vytlacil (2007) and more recently by Brinch, Mogstad, and Wiswall (2017) to produce a more complete picture of the effects of heterogeneity (Cornelissen, Dustmann, Raute, & Schnberg, 2016).

4.2. Marginal treatment effect framework

The marginal treatment effect framework centers on the generalized Roy model. It is based on a potential outcomes model and a latent variable discrete choice model for selection into treatment (Heckman & Vytlacil, 2005, 2007; Brinch et al., 2017). This framework links the unobserved heterogeneity in the treatment effect to the unobserved heterogeneity in the propensity of taking the treatment. In other words, the treatment effect depends on each individual's unobserved taste or distaste for treatment (resulting from a net benefit/cost of treatment).

The potential outcomes model accommodates two regimes based on a binary indicator D for treatment status (adoption of SRI or not).

$$\begin{aligned} \text{Regime } 0: Y_0 &= \beta_0 X + U_0 \text{ if } D = 0 \\ \text{Regime } 1: Y_1 &= \beta_1 X + U_1 \text{ if } D = 1, \end{aligned}$$

where (Y_0) and (Y_1) denote two potential outcomes (e.g., mean, variance and skewness of yield) for untreated $(D = 0)$ and treated $(D = 1)$ farmers, respectively; X is a vector of covariates that influences the outcome in each regime; the error terms U_0 and U_1 capture all unobserved factors that affect the outcomes in each regime such that $\mathbb{E}(U_0|X) = \mathbb{E}(U_1|X) = 0$.[14]

The treatment selection process is modeled by an index threshold-crossing model that captures the latent net benefit of choosing the treatment (D^*). It depends on observed determinants of selection into treatment (X, Z) (where Z is an instrument and is therefore excluded from the outcome Eqs. (3) and (4)), and on an unobserved component (V) such that:

$$D^* = \gamma_x X + \gamma_z Z - V \quad \text{and} \quad \mathrm{D} = \mathbf{1}(\mathrm{D}^* > 0) = \mathbf{1}(\mathrm{P(Z)} > \mathrm{U_D}),$$

where $P(Z) \equiv Pr(D = 1|X, Z) = Pr(\gamma_x X + \gamma_z Z > V) = F_V(\gamma_x X + \gamma_z Z)$ denotes the propensity score given (X, Z) (i.e., the probability a farmer will receive treatment), with F_V being the cumulative distribution function of V; and $U_D \equiv F_V(V) \sim \mathscr{U}[0, 1]$ (standard uniform distribution) and corresponds to different quantiles of V, that is, here, the propensity not to be treated. The unobserved component V is modeled as a negative shock that reduces the likelihood of treatment, and can be interpreted as unobserved "resistance" (or "distaste") to take treatment.[15] The treatment assignment Eq. (1) suggests that farmers choose to be treated whenever the propensity score exceeds the quantile of the distribution of V; in other words, whenever "observed encouragement" exceeds "unobserved resistance" to treatment (Cornelissen et al., 2016).

Given this framework, the marginal treatment effect is defined as the expected treatment effect conditional on covariates $X = x$ and unobserved resistance to treatment $U_D = u$ (Heckman & Vytlacil, 2005, 2007):

$$MTE(x, u) = \underbrace{x(\beta_1 - \beta_0)}_{\text{observed}} + \underbrace{k(u)}_{\text{unobserved}} \tag{2}$$

where $k(u) \equiv \mathbb{E}(U_1 - U_0|U_D = u)$ is the component of the treatment effect that varies across the unobserved resistance to treatment. The MTE function described by expression (2) implies that the treatment effect for farmers with the same observed characteristics $X = x$ may differ if they experience different unobserved resistance to treatment $U_D = u$. For instance, given X, farmers with lower values of U_D are more likely to take treatment, regardless of the realization of Z.[16] A MTE function that is declining in u would therefore indicate that farmers who are more likely to choose $D = 1$ (in this application, to adopt SRI) also experience larger gains in outcome Y from receiving the treatment (Mogstad and Torgovitskyz, 2018).

[14] For the sake of exposition, we present here a simplified linear version of the MTE model. Note that this model accommodates general functionals such that $Y_0 = \mu_0(X) + U_0$ if $D = 0$ and $Y_1 = \mu_1(X) + U_1$ if $D = 1$, where $\mu_0(X) = \mathbb{E}(Y_0|X)$ and $\mu_1(X) = \mathbb{E}(Y_1|X)$ are allowed to be non-linear.

[15] Note that if we had instead modeled the latent variable in Eq. (1) as $D^* = \gamma_x X + \gamma_z Z + V$ (with a '+' sign before V rather than the conventional '–' sign), then higher values of U_D would suggest increased propensity to treatment.

[16] This is because by Eq. (1), a lower U_D makes the event $P(Z) > U_D$ more likely, ceteris paribus.

Identification of this model hinges on a number of assumptions detailed in Heckman and Vytlacil (2005, 2007).[17] Identification, however, does not require covariates X to be exogenous in that they are allowed to be correlated with $U_0, U_1,$ and V (Heckman & Vytlacil, 2005), in contrast to the assumptions commonly made in the selection literature or the classical two-stage least squares (2SLS).

4.3. Estimation strategy

Heckman and Vytlacil (2007) and Brinch et al. (2017) propose an estimation strategy based on the so-called separate estimation approach. This entails a two-step procedure. The first step consists of estimating the propensity score $P(Z)$ using a probit, logit, or linear probability model. A fully non-parametric model is also possible, although data requirements makes it impractical in our case. The second step is the estimation of the conditional expectations of Y_0 and Y_1 in the sample of untreated and treated, i.e., $\mathbb{E}(Y_0|X, P(Z), D = 0)$ and $\mathbb{E}(Y_1|X, P(Z), D = 1)$:

$$\mathbb{E}(Y_0|X = x, P(Z) = p, D = 0) = x\beta_0 + \mathbb{E}(U_0|U_D > p) \tag{3}$$
$$\mathbb{E}(Y_1|X = x, P(Z) = p, D = 1) = x\beta_1 + \mathbb{E}(U_1|U_D \leqslant p) \tag{4}$$

The difference between the two conditional expectations yields the MTE:

$$\begin{aligned} MTE(x, u) &= \mathbb{E}(Y_1|X = x, U_D = u) - \mathbb{E}(Y_0|X = x, U_D = u) \\ &= x(\beta_1 - \beta_0) + k_1(u) - k_0(u) \end{aligned} \tag{5}$$

where $k_j(u) = \mathbb{E}(U_j|U_D = u)$, for $j = 0, 1$ are functions defined for $p = u$ to be estimated either parametrically or non-parametrically. The MTE is therefore interpreted as the expected treatment effects for individuals indifferent between being treated or not with covariates $X = x$ and propensity score $P(Z) = p = U_D$. It can also be interpreted as a willingness-to-pay measure when outcomes are values under alternative treatment regimes.

The separate estimation approach is particularly versatile in that it allows for both continuous and categorical instruments. Brinch et al. (2017) show that, under a binary instrument, which induces only two values of $P(Z)$ for each value of X, the separate estimation approach can identify a linear MTE model that allows for treatment heterogeneity and self-selection based on unobserved gains from treatment.

Finally, an important contribution of this literature is to develop a unifying framework that links the MTE estimator to common treatment effect parameters such as the average treatment effect (ATE), the average treatment on treated (ATT) and the average treatment on untreated (ATUT). Heckman and Vytlacil (2005) show that all three treatment effects parameters can be expressed as weighted averages of the marginal treatment effect such that:

$$\begin{aligned} ATE(x) &= \mathbb{E}(Y_1 - Y_0|X = x) = \int_0^1 MTE(x, u)\omega_{ATE}(x, u)du \\ ATT(x) &= \mathbb{E}(Y_1 - Y_0|X = x, D = 1) = \int_0^1 MTE(x, u)\omega_{ATT}(x, u)du \\ ATUT(x) &= \mathbb{E}(Y_1 - Y_0|X = x, D = 0) = \int_0^1 MTE(x, u)\omega_{ATU}(x, u)du \end{aligned}$$

where the weights are given by: $\omega_{ATE}(x, u) = 1$, $\omega_{ATT}(x, u) = \frac{\int_u^1 f(p|X=x)dp}{\mathbb{E}(P|X=x)}$, and $\omega_{ATU}(x, u) = \frac{\int_0^u f(p|X=x)dp}{\mathbb{E}((1-P)|X=x)}$, with $f(p|X = x)$ being the density of the propensity score.

These weights indicate that $ATE(x)$ samples U_D uniformly while $ATT(x)$ overweighs low values of U_D in that it oversamples farmers

[17] These assumptions include: (1) Conditional Independence: (U_0, U_1, V) are statistically independent of Z given X; (2) Rank condition: $Pr(D = 1|X, Z) = \mu(X, Z)$ is a nontrivial function of Z given X; (3) Separability: $\mathbb{E}(U_j|X, U_D) = \mathbb{E}(U_j|U_D)$ for $j = 0, 1$; (4) Letting X_d denote a value of X if $D = d$, $X_1 = X_0$ almost everywhere.

who are most likely to participate in the intervention (i.e., those with low values of u). By contrast, $ATUT(x)$ overweighs high values of U_D in that it oversamples farmers who are least likely to participate in the intervention (i.e., those with high values of u).

4.4. Marginal treatment effect of SRI

We apply this framework to our data. The decision to adopt the system of rice intensification is observed and captured by the dummy variable *SRI*, which takes value 1 in the case of adoption and value of 0 otherwise. Given observed and unobserved characteristics, a farmer elects the new SRI technology whenever his latent (unobserved) expected benefits from adoption (SRI^*) are positive, and abstains otherwise. We model the first stage selection equation as follows:

$$\begin{aligned} SRI^* &= \gamma_x X + \gamma_z Z - V \\ SRI &= \begin{cases} 0 & \text{if } SRI^* \leq 0 \\ 1 & \text{if } SRI^* > 0 \end{cases} \end{aligned}$$

where (X, Z) is a vector of exogenous variables affecting the probability of adopting SRI. These variables include (i) household characteristics such as education, experience in rice growing, and wealth; (ii) farm characteristics such as farm size, fertility of the soil, slope of the terrain, and input use (employed labor and amount of seed use); (iii) social network and extension services; and (iv) perception about changing climatic patterns, which is a novelty in the SRI literature (see for example Takahashi & Barrett, 2013; Noltze et al., 2013). Some covariates X such as labor, quantity of seeds, and access to extension services are likely to be correlated with the selection equation unobservables V. As discussed above, under our assumptions, the model is identified even with endogenous covariates (Heckman & Vytlacil, 2005).

To address sample selection bias, we assume that at least one element of the vector of covariates Z in the SRI equation is excluded from the outcome equation. Farmers' climate change perception, in particular farmers' perception of reduced rainfall, is one such instrument. It is a binary variable that takes value 1 if a farmer believes that rainfall has decreased over the last 10 years, and 0 otherwise. It is conceivable that farmers who believe that rainfall has decreased over the last 10 years are more likely to respond by adopting water-saving and climate change mitigating practices such as SRI. We expect therefore perception of changing climatic patterns to correlate with the treatment assignment. Our exclusion restriction is that farmers' perception of reduced rainfall does not affect the outcomes (the first three central moments of rice yield) directly but through the SRI adoption decision. We also include the interactions (Perception of reduced rainfall $\times$ Village of residence) as additional instruments because climate perception differs from one village to another, as discussed earlier. We follow the applied literature on MTE in conducting a joint significance test of all instruments (cf. Carneiro, Heckman, & Vytlacil, 2011; Brinch et al., 2017; Cornelissen, Dustmann, Raute, & Schnberg, 2018).

The second stage outcome equations and resulting MTE are therefore estimated using the separate estimation approach, as described above. They follow from Eqs. (3)–(5). As noted before, following Kim and Chavas (2003), we estimate our MTE model for the first three central moments of rice yield.

5. Results and discussion

We estimate the impact of SRI on the first three moments of yield (i.e., mean, variance, and skewness) using marginal treatment effects models. We report the two stages of our model in Tables 2 and 3. The choice of variables in the estimation draws on the theoretical and empirical variables in Di Falco and Chavas (2009), Noltze et al. (2013), Abdulai and Huffman (2014) and Alem et al. (2015). We first discuss the correlates of SRI adoption, and, follow this with an examination of the determinants of the mean, variance, and skewness for rice yield.

Table 2
SRI Adoption Decision Model: Average Derivatives.

	(1) Average Partial Effect	
	Coefficient	SE
Household size	0.085	(0.101)
Age of household head	0.002	(0.020)
Education of household head (years)	0.057	(0.067)
Rice farming experience of head (years)	0.032***	(0.012)
Wealth (log wealth)	0.375**	(0.177)
Total labor supply (man days)	0.004	(0.004)
Seed rate usage (kg/acre)	−0.095***	(0.025)
Plot size (acre)	−1.252***	(0.316)
Very fertile (Yes = 1)	0.253	(0.242)
Gently sloping plot (Yes = 1)	0.315	(0.302)
Plot distance (km)	0.012	(0.034)
Distance to market (minutes)	0.001**	(0.001)
Change crop		
Yes	0.314	(0.215)
Unsure	−0.884**	(0.349)
Social connection	1.631***	(0.209)
Extension frequency visits	0.437***	(0.108)
Perception Reduce Rainfall	3.263***	(1.189)
Chisano × Perception reduced rainfall	−3.214***	(1.203)
Chita × Perception reduced rainfall	−3.357**	(1.524)
Ikule × Perception reduced rainfall	−2.747**	(1.359)
Mngeta × Perception reduced rainfall	−1.394	(0.898)
Lukolongo × Perception reduced rainfall	−3.424***	(1.312)
Mchombe × Perception reduced rainfall	−2.903***	(1.035)
Constant	−4.032	(2.599)
Village Fixed Effect	Yes	
Test for joint significance of IVs		
Chi-square	361.79	
p-value	0.000	
Observations	305	
Number of Villages	8.000	
Log Pseudo-Likelihood	−69.254	
Pseudo R2	0.666	

This table reports the average partial effects evaluated at the mean value of each variable from the probit model. The dependent variable is the probability of adopting SRI. Bootstrapped (250 reps) standard errors clustered at the village level are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Chi-square and p-values indicate the results of the test of joint significance of coefficients on the instrumental variables.

5.1. Determinants of SRI adoption

We begin by shedding some light on the observed factors that characterize SRI adopters. To control for selection bias, we use farmer's perception of climate change, as measured by their perception of reduced rainfall in the last 10 years, as an instrument, and interact it with the farmer's village of residence. The results show that reduced rainfall perception is a strong predictor of the likelihood that a farmer adopts SRI. This suggests that adoption of SRI could be regarded as an adaptation mechanism to climate change, since one of its key objectives is to reduce water usage in rice farming. The interaction effects are, however, negative and mostly significant which likely suggests that a farmer's decision to adopt depends on the net effect. We perform a test of joint significance of the coefficients of the instruments and find the values of the chi-square (361.79) and p-value (0.000) indicate that the instruments all together are statistically significant.

We find that wealthier households, with more experience growing rice, and whose plots are situated closer to their homesteads are more likely to adopt SRI. Although SRI seeks to help

Table 3
Determinants of Yield and SRI: Marginal Treatment Effect Regression Model.

	(1) Yield		(2) Yield Variance		(3) Yield Skewness	
Panel A: β_0	Coefficient	SE	Coefficient	SE	Coefficient	SE
Household (Hh) size	−0.021	(0.019)	0.003	(0.008)	−0.004	(0.006)
Age Hh head	−0.002	(0.003)	−0.000	(0.001)	−0.000	(0.001)
Education Hh head	−0.013	(0.015)	−0.005*	(0.003)	−0.000	(0.004)
Rice experience Hh head	−0.001	(0.002)	0.000	(0.001)	0.000	(0.001)
Wealth (log wealth)	0.064**	(0.025)	−0.023*	(0.013)	0.019**	(0.009)
Total labor (man days)	−0.001	(0.001)	0.000	(0.000)	−0.000	(0.000)
Seed rate usage (kg/acre)	0.002	(0.003)	−0.001	(0.001)	0.001	(0.001)
Plot size (acre)	−0.007	(0.018)	0.002	(0.014)	−0.003	(0.012)
Very fertile (Yes = 1)	−0.010	(0.050)	0.022	(0.022)	−0.010	(0.017)
Gently sloping plot (Yes = 1)	0.111**	(0.055)	−0.059*	(0.034)	0.035**	(0.017)
Plot distance (km)	−0.000	(0.004)	−0.004	(0.003)	0.002	(0.002)
Distance to market (minutes)	−0.000	(0.000)	0.000	(0.000)	−0.000	(0.000)
Change crop						
Yes	0.002	(0.052)	0.017	(0.017)	−0.012	(0.016)
Unsure	0.069	(0.220)	−0.063	(0.102)	0.042	(0.232)
Social connection	−0.012	(0.100)	0.037	(0.029)	−0.008	(0.020)
Extension frequency visits	0.036	(0.059)	0.048***	(0.015)	−0.014	(0.020)
Constant	0.232	(0.410)	0.412**	(0.180)	−0.212	(0.139)
Village fixed effects	Yes		Yes		Yes	
Panel B: $\beta_1 - \beta_0$						
Household (Hh) size	0.028	(0.024)	0.008	(0.020)	0.059	(0.046)
Age Hh head	0.007	(0.006)	0.007	(0.005)	0.017	(0.010)
Education Hh head	0.071**	(0.028)	0.025	(0.018)	0.051	(0.033)
Rice experience Hh head	0.000	(0.003)	−0.012**	(0.006)	−0.017	(0.012)
Wealth (log wealth)	−0.016	(0.035)	0.062	(0.051)	0.067	(0.076)
Total labor (man days)	0.001	(0.001)	−0.001	(0.001)	−0.002	(0.003)
Seed rate usage (kg/acre)	−0.002	(0.010)	0.000	(0.010)	0.015	(0.026)
Plot size (acre)	−0.203**	(0.089)	−0.205	(0.131)	−0.467	(0.349)
Very fertile (Yes = 1)	−0.012	(0.049)	0.030	(0.074)	0.055	(0.198)
Gently sloping plot (Yes = 1)	−0.268**	(0.112)	−0.027	(0.076)	−0.214***	(0.076)
Plot distance (km)	−0.002	(0.010)	0.008	(0.008)	−0.013	(0.016)
Distance to market (minutes)	0.000	(0.000)	−0.000	(0.000)	0.000	(0.000)
Change crop						
Yes	0.102	(0.066)	0.108**	(0.054)	0.271*	(0.149)
Unsure	−0.103	(0.300)	−0.031	(0.188)	−0.279	(0.350)
Social connection	0.324	(0.242)	0.567*	(0.295)	1.358*	(0.792)
Extension frequency visits	0.019	(0.057)	0.019	(0.038)	0.144**	(0.072)
Constant	−0.476	(0.670)	−1.508	(1.040)	−2.769	(2.105)
Village fixed effects	Yes		Yes		Yes	
$k(p = u)$	−1.520***	(0.464)	−1.617**	(0.801)	−3.516*	(2.127)
Observations	305		305		305	
Number of Villages	8		8		8	
P-Value observable heterogeneity	0.000***		0.000***		0.000***	
P-Value essential heterogeneity	0.001***		0.044**		0.098*	

Notes: Coefficients β_0 in Panel A reflect the average differences in outcomes across covariates for the non-adopters of SRI; on the other hand, coefficients $\beta_1 - \beta_0$ in Panel B can be interpreted as differences in treatment effects across covariate values, just like an interaction between treatment status and a covariate in an ordinary least-squares regression. Bootstrapped (250 reps) standard errors clustered at the village level are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

poorer farmers enhance their yields and reduce water consumption, somewhat unexpectedly, wealthier farmers are among the early adopters. This could be because wealthier farmers are better equipped to absorb risk from experimenting with new technologies. Regarding the influence of inputs, we find that increased labor requirement is positively associated with SRI adoption, though statistically indistinguishable from zero.[18] As expected, reduced seeds usage is associated with increased SRI adoption, and so is reduced land size. A possible explanation is that farmers may be experimenting before considering a scale up of this practice.[19] An alternative explanation could be that farmers are simply diversifying their portfolio of technology. It is also possible that, like in other settings and regions (e.g., Madagascar), farmers have dedicated only small plots to SRI, despite its expected benefits, because of the high opportunity costs associated with this practice (Moser & Barrett, 2003).

Greater interaction with extension services, measured by frequency of visits, influences the adoption decision positively, which is likely due to the complex and counterintuitive nature of SRI. In addition, greater social connection (as measured by the number of social groups of the farmer) is associated with technology adoption. Finally, and unexpectedly, the likelihood of adopting SRI is

[18] Although, in this sample, adopters demand considerably more labor than non-adopters, as indicated in Table 1, the effect of labor is not a determinant for the adoption of SRI in our sample. Overall, the evidence suggests that SRI is labor-intensive when farmers are still unfamiliar with the practice (Barrett et al., 2004), with extra labor particularly needed for land preparation, seed sorting, transplanting and weeding (Thakur & Uphoff, 2017; Moser & Barrett, 2003; Moser & Barrett, 2006). Subsequently, as they understand the technology better, labor requirement is reduced (Uphoff, 2006; Barrett et al., 2004; Gathorne-Hardy et al., 2016).

[19] Note that SRI was introduced in the Morogoro region in 2006 for the first time. This survey was undertaken in June 2013. As a result, most adopters had implemented SRI for a couple of years at most.

insensitive to some of individual and household characteristics, such as education level, household size, inputs such as total labor supply, and plot characteristics such as the slope and soil fertility.

5.2. Treatment effects with observed characteristics

We estimate the effect of adopting SRI on expected yield, yield variance and yield skewness for non-adopters and adopters, based on equations (3) and (5). The estimation results are presented in column (1) through (3) of Table 3, using Andresen's (2018) 'mtefe' command in Stata. To have a comprehensive picture of the effects of SRI adoption on the entire sample, the coefficients β_0 for non-adopters are reported in Panel A in line with Eq. (3), whereas the treatment effects $\beta_1 - \beta_0$ for adopters are presented in Panel B in line with Eq. (5).[20]

For untreated households, the effect of wealth on the first three central moments of yield suggests, that among untreated farmers, wealth contributes toward increased rice productivity (+6.4 percent) while reducing yield dispersion (−2.3 percent) and reducing downside risk exposure (+1.9 percent). The effect of wealth on variability and on skewness reinforce each other, which unambiguously reduces the cost of risk bearing (Di Falco & Chavas, 2009) for risk averse farmers.[21] All three coefficients are statistically significant, at the 5% level for expected yield and the skewness, and at the 10% level for the variance. However, the treatment effect of a wealthier farmer is statistically no different (across all three moments) from that of a poorer farmer. Thus, although wealthier farmers are more likely to adopt SRI, adoption does not give them any additional benefit (or cost for that matter) relative to poorer farmers. In this respect, our finding implies that SRI adoption does not discriminate along wealth lines. However, this finding does not lend support to the assertion of the pro-poor nature of SRI, since there is no evidence of a negative treatment effect for wealth, which would imply that SRI adoption helps poorer farmers bridge the gap with wealthier farmers in terms of expected yield, variability, and exposure to downside risk.

We also find that non-adopters with gently sloping plots as opposed to flat plots are, on average, 11 percent more productive, and experience a 6 percent uncertainty reduction (i.e., reduction in yield variability), and a 3.5 percent reduction in downside risk exposure (i.e., increased skewness). These effects are all statistically significant. The effect of gently sloping plots on all three moments of yield are qualitatively similar to the effect of wealth. In particular, we observe a decrease in cost of risk given the reduction in variance and the increase in skewness for non-adopters.[22] Interestingly, this advantage disappears for those who adopt SRI. Indeed, for expected yield and skewness, adopters who cultivate on gently sloping plots display treatment effects that are 27 and 21 percent lower than those with flat plots, respectively. This may be because, under SRI, young seedlings which are planted shallowly are transplanted. If the water level is not equal due to the slope of the plot, some of the transplanted seedlings may not take root, or some seedlings may be submerged in water, resulting in poor growth.[23]

Moreover, although for non-adopters, the size of the farm has no effect on yield, SRI adopters are more likely to grow rice on smaller fields and reap the benefit in the form of a 20-percent yield increase. This finding suggests that due to the high care required by SRI, farmers with large plots are unable to implement the full system, consequently leading to lower yields. This result is consistent with the literature that posits an inverse relationship between farm size and productivity (Binswanger, Deininger, & Feder, 1995; Abdulai & Huffman, 2014) and argues that, in this respect smaller farms tend to be more productive than their larger counterparts.

Training (education), experience in rice farming and information dissemination play an important role in adoption of SRI. We find that one more year of education reduces yield variability for non-adopters' but does not affect either expected yield or yield skewness. In contrast, an additional year of education increases adopters' yield by 7.1 percent, but has no impact on yield variability or skewness. A farmer's education level may not be consequential for variability and skewness here because the counterintuitive nature of SRI primarily requires continuous on-the-job training and expert advice to fully reap of the benefits of the practice. An additional year of experience in rice farming reduces the yield variability experienced by adopters vs non-adopters. We find too, that, in the untreated state, more frequent extension visits, which provide professional support and advice, increase yield variability without affecting expected yield or skewness. However, in the treated state, more frequent visits from extension services result in reduced risk of crop failure (increase in skewness), which highlights the importance of the services provided by extension workers.

The density of social networks has no significant treatment effect on expected yield, but does increase the treatment effect on both yield variability and skewness. This finding suggests that denser social connections shield SRI adopters from the downside risk of crop failure, although they are faced with increased yield variability. The larger effect on yield skewness than on variability indicates an overall reduction in the cost of risk bearing for farmers (Di Falco & Chavas, 2009). Qualitatively, we find a similar pattern when SRI adopters undertake adaptation measures in the form of changes in their crop portfolio as a result of perceived reduced rainfall. The larger effect on skewness means that adopters who carry out such adaptation strategies hedge against downside risk (e.g., the risk of crop failure). Huang, Wang, and Wang (2015) find similar effects for China, although, in their case, the effects of adaptation measures on yield variability and skewness reinforce each other.

In brief, for non-adopters, both wealth and gently sloping plots are key determinants across all outcomes. The effects of both covariates are to unambiguously improve rice productivity and reduce the cost of risk bearing (through both reduced variance and increased skewness). For adopters, on the other hand, social networks and changes in crop portfolios (as an adaptation strategy) are two critical covariates that result in both increased yield variance and yield skewness. However, the larger treatment effect on skewness indicate an overall reduction in the cost of risk (Huang et al., 2015; Di Falco & Chavas, 2009). Further, the significance of the treatment effects resulting from the covariates in all three central moments equations suggests the presence of observed heterogeneity in the sample. We perform a test of joint significance of the coefficients of the covariates $(\beta_1 - \beta_0)$for the yield, yield variability, and yield skewness (see Eq. (5)). The *p*-

[20] Treatment effects $\beta_1 - \beta_0$ are estimated by taking the difference between Eq. (4) and (3). They can be "interpreted as differences in treatment effects across covariate values, just like an interaction between treatment status and a covariate in an ordinary least-squares regression" (Andresen (2018)).

[21] It is worth noting that these farmers exhibit decreasing absolute risk aversion (DARA) since their wealth tends to reduce their risk premium or private cost of bearing risk (Di Falco & Chavas, 2009).

[22] We typically expect plots with favorable biophysical characteristics (flat plots, fertile soil, brown/brown-black soil color) to be positively associated with agricultural yield and to contribute positively to reducing yield risk. In this respect, our finding that gently sloping plots contribute significantly to enhancing yield and reducing yield risk is counter-intuitive. However, these results might be explained by the possibility that gently sloping plots could have higher proportion of conservation structures which may improve productivity and mitigate risk.

[23] We thank an anonymous reviewer for suggesting this explanation.

value (0.000) indicates that the treatment effect differs across X at the 1 percent level of significance.

5.3. Estimation of MTE – the role of unobserved characteristics

We now plot the estimated marginal treatment effects (see Eq. (5)) for rice yield, yield variability, and yield skewness, as a function of the unobserved component of treatment choice, U_D. These MTE curves (see Fig. 2) are evaluated at the mean value of X and show a 90 percent confidence interval band and the average treatment effect (ATE) line. While the average treatment effects are constant, all three MTE curves are monotonically declining in U_D, indicating that farmers with lower values of U_D enjoy larger gains from adopting SRI. On the other end of the spectrum, farmers with higher values of U_D receive smaller returns (and at times even negative returns) from treatment.

Fig. 2a depicts the MTE curve for rice yield. It shows that farmers who are most inclined/least resistant to adopt SRI (those with low values of U_D) enjoy high, positive marginal treatment effects amounting up to 80% (See Table 5 in the Appendix).[24] By contrast, farmers with particularly high values of U_D who are most reluctant to adopt SRI incur negative yield returns of up to −66% by adopting SRI.[25] The MTE curve for yield variability (Fig. 2b) shows that farmers who are most likely to adopt SRI (i.e., farmers with low U_D) experience a statistically significant increase in yield volatility by up to 49%. Conversely, farmers who are more resistant to adopting SRI (farmers with high U_D) experience a statistically significant reduction in yield variability by up to 109%. Thus, farmers who are most inclined to adopt SRI appear to face increased production risk. The risk-enhancing feature of SRI is consistent with Barrett et al. (2004) and could result from the inclusion of the high-yielding variety (Saro 5) in the SRI package. However, Fig. 2c shows that such farmers (with low U_D) experience an increase in yield skewness, and therefore a reduction in exposure to downside risk, by up to 128%. In contrast, farmers who are most reluctant to adopt SRI (with high U_D) face a considerably higher probability of crop failure by adopting SRI as they incur reduced yield skewness reaching over 200%. These outcomes indicate that, in addition to the distribution of rice productivity, accounting for the distribution of production risk (both in terms of yield variability and downside risk) is crucial to understand individual farmers' choice.

Finally, our findings suggest considerable heterogeneity in outcomes resulting from the adoption of SRI among farmers with different unobserved factor U_D. The presence of heterogeneity in outcomes can be seen in the declining MTE curves (as compared with the homogenous ATE horizontal line). It can also be substantiated by performing a test of joint significance of the coefficients of $k(u) = k_1(u) - k_0(u)$ in Eq. (5) for yield, yield variability, and yield skewness. The resulting p-values 0.001, 0.044, and 0.098, respectively, indicate the presence of essential heterogeneity at the 1, 5, and 10 percent level. This test provides evidence that the marginal treatment effects are highly heterogeneous and suggests that farmers self-select (at least partially) based on the knowledge of their unobserved idiosyncratic gains.

5.4. Conventional treatment parameters

We now aggregate over the MTE curves to obtain the standard treatment effect parameters as discussed in Section 4.2. Table 4 reports the estimation of four treatment effect parameters, namely, the average treatment effect (ATE), the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATUT), and the marginal policy return and treatment effect (MPRTE). Column (1) shows the treatment effect for mean yield. We find that for the average treated farmer, adoption raises the probability of higher yield by nearly 43 percent. The magnitude of the ATT is large and statistically significant, and is in line with similar studies in Tanzania (Alem et al., 2015). We find positive but insignificant ATE, and negative but insignificant ATUT.

By contrast, in Column (2), the ATE and ATUT for yield variance are both negative and statistically significant, at the 5 percent level. That is, a randomly picked farmer on average experiences a 30 percent reduction in yield variability. Additionally, the average untreated farmer would experience a decrease in yield variance of approximately 76 percent by adopting SRI. The magnitude of ATUT is larger than the ATE, suggesting that the level of risk attenuation is higher for non-adopters, which is consistent with a declining MTE curve for yield variability. The size and sign of the ATUT for yield variability suggest that a policy inducing every untreated farmer to adopt SRI would likely mitigate the uncertainty about yield dispersion faced by untreated risk averse farmers, thereby enhancing their welfare. Accordingly, we estimate the marginal policy-relevant treatment effect, which assesses the impact of a policy intervention that has an effect similar to a shift in one of the components of the instruments Z (Carneiro, Heckman, & Vytlacil, 2010; Carneiro et al., 2011). In particular, a policy instrument that is capable of raising awareness about changing rainfall patterns in farming communities would contribute to reduce yield variability by nearly 52 percent.

Finally, in Column (3) the treatment effects for yield skewness reveals that the ATT is positive and significant, at the 5 percent level. The result indicates that, for an average treated farmer, adopting SRI reduces the probability of exposure to a downside risk by 28.3 percent. We do not find that adopting SRI has significant ATE, ATUT and MPRTE for the skewness of rice yield.

These average treatment effects point to the undeniable benefits that the average farmer may expect to reap by adopting SRI. However, since we allow farmers to differ both in observed and unobserved characteristics, the distribution of the expected benefits, rather than the average benefits, will likely shape their adoption decision.

5.5. Robustness

The downward sloping pattern on the MTE of SRI for the three central moments is robust to distributional and specification changes as well as to outliers, as can be seen in Fig. 3. First, all the estimations reported and discussed throughout the analysis, our baseline specifications, include the five outliers identified in Section 3. The baseline MTEs for expected rice yield, yield variance, and yield skewness (full lines in Fig. 3a, b and c respectively), are robust to the exclusion of these outliers (dashed lines). Second, our findings are also robust to changes in the distribution of the error term of the selection equation (SRI equation). Using a logit function (dotted-dashed lines) instead of a probit function (for the baseline MTEs) yield similar results. Allowing for a quadratic MTE, which enables a non-linear MTE (dotted lines), instead of our baseline linear MTE does not change the pattern of the distribution of benefits.[26] Consequently, the basic pattern in which gains from SRI adoption depend on unobserved treatment heterogeneity (captured by the MTE curves) is a robust phenomenon regardless of the particular specification and the exclusion of outliers.

[24] All the figures reported below in this section come from Table 5 (Appendix).

[25] Note that 55 percent of farmers ($U_D < 0.55$) enjoy positive returns while the remaining 45 percent incur negative returns.

[26] Brinch et al. (2017) show that the separate estimation approach identifies a quadratic MTE model, in the presence of a binary instrument Z and a binary covariate X.

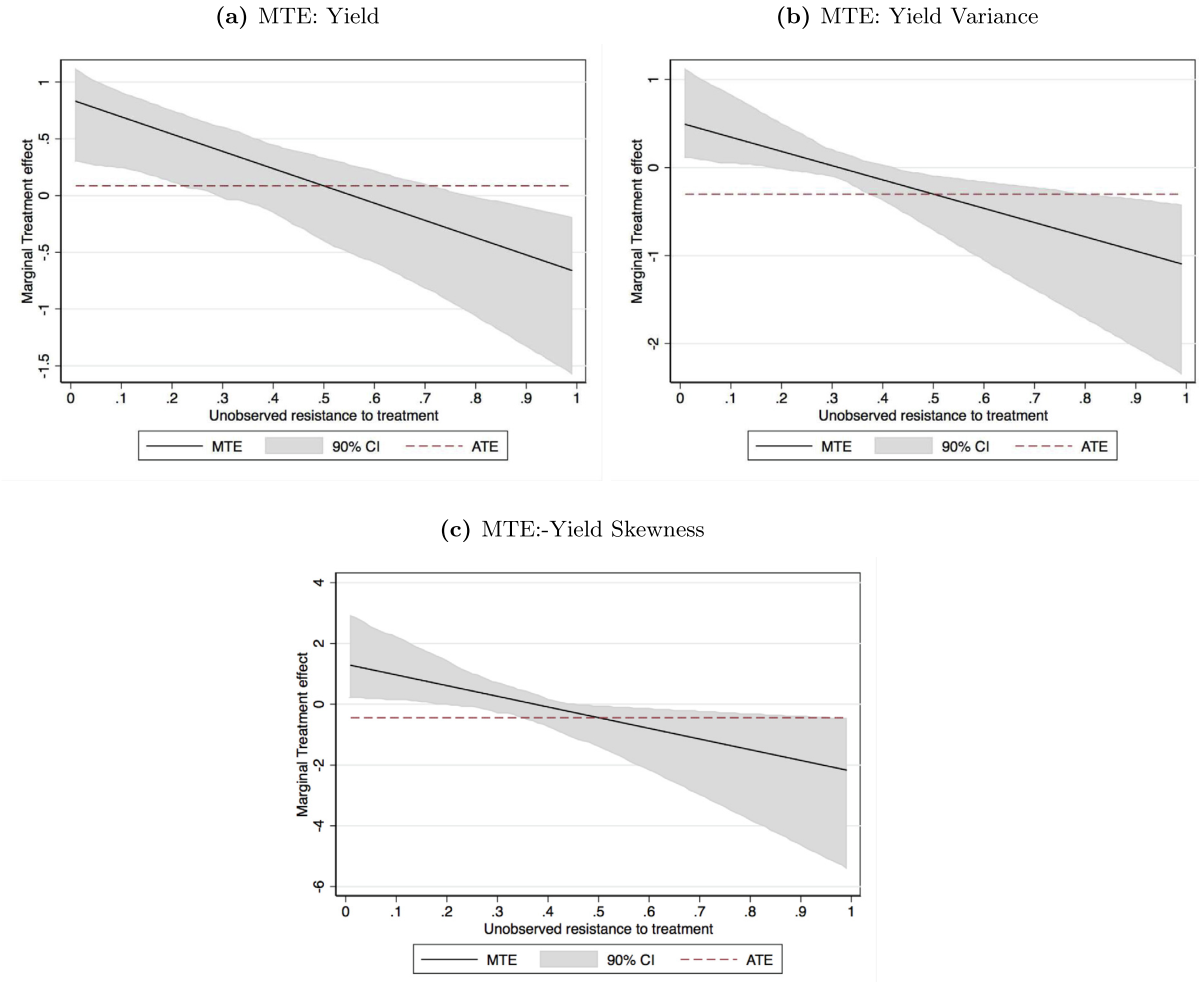

Fig. 2. Marginal Treatment Effects of Yield, Yield Variability and Yield Skewness.

Table 4
Average Treatment Effects & Policy Effects.

	(1) Yield		(2) Yield Variance		(3) Yield Skewness	
Effects	Coefficient	SE	Coefficient	SE	Coefficient	SE
ATE	0.085	(0.179)	−0.301**	(0.152)	−0.442	(0.359)
ATT	0.427***	(0.159)	0.019	(0.068)	0.283**	(0.133)
ATUT	−0.403	(0.298)	−0.758**	(0.377)	−1.476	(0.931)
MPRTE	0.026	(0.244)	−0.517**	(0.245)	−0.883	(0.588)

Notes: The table reports, for our three outcomes rice yield, rice yield variability and rice yield skewness, the average treatment effect (ATE), the average treatment on the treated (ATT), the average treatment effect on the untreated (ATUT), and the marginal policy relevant treatment effects (MPRTE). Bootstrapped (250 reps) standard errors clustered at the village level are reported in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.6. Caveat

An alternative interpretation of our results is that our measures of riskiness are not entirely satisfactory. Although the study considers the impact of SRI on the variance of yield and takes this to imply an increase in risk, it is likely that our second and third central moments do not capture risk exposure alone. They could also capture heterogeneity among households on other dimensions including farming ability, motivation, and preferences. This heterogeneity might make it difficult for farmers to also disentangle the true riskiness of this new technology from the characteristics of adopting farmers. With such a noisy signal, social learning about the new technology could be particularly slow, which could also explain low adoption rates.[27] This might partly explain why the plot size for adopters is much smaller than that of non-adopters.In brief, the farmers' difficulty in assessing risk may lead to slow learning and

[27] On this point, Fafchamps (2010) argues that *"It is empirically difficult to formally test theories that relate to decisions made by poor households with the relative riskiness of the options available to them. There are two main reasons for this. First, it is very difficult to obtain measurable variation in risk across individuals. The reason is that, by definition, risk materializes over time. Consequently, a lot of information is required to construct reasonable measures of risk. Secondly, even when measures of riskiness can be constructed, sufficient exogenous variation in risk must be available to distinguish what can reasonably be attributed to risk as opposed to other features typically correlated with risk."*

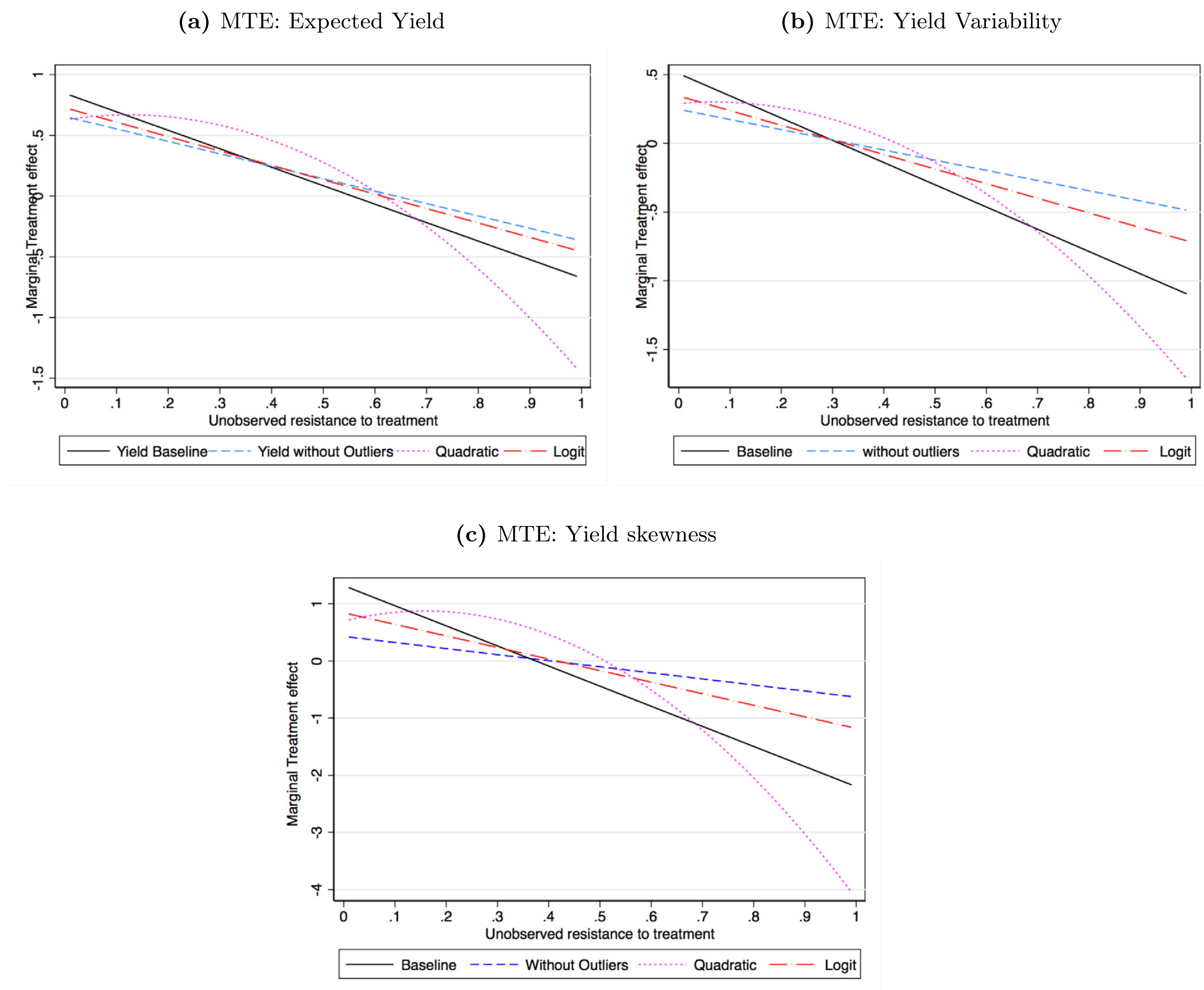

Fig. 3. Robustness Checks: Marginal Treatment Effects.

therefore slow adoption, which in turn may explain why only marginal land areas are allocated to SRI.

Another caveat pertains to the external validity of our findings. Because SRI is a very flexible technology that can adapt to local agro-ecological conditions, almost on a micro-scale, context-specific outcomes are to be expected. Our findings may well be specific to the practice of SRI in small scale rainfed rice fields, and may therefore not be generalizable to situations where alternative SRI packages that rely on irrigation are adopted. Nonetheless, this study may provide lessons applicable to other rain dependent rice farmers, who constitute the majority of African farmers.

6. Conclusion

This paper presents an impact evaluation analysis of the introduction of the system of rice intensification (SRI) in Morogoro (Tanzania), with a focus on expected yield, yield variability and yield skewness (exposure to downside risk). Using a marginal treatment effects model, we estimate jointly the decision to adopt SRI adoption and its impact on the first three central moments of rice yield, to shed some light on the puzzling low rates of SRI adoption in Africa, despite its yield-enhancing property and its pro-poor agenda. On aggregate, our results show that an average adopter experiences a 42.7 percent rise in rice productivity and a 28.3 percent reduction in the probability of crop failure, and no effect on yield variability (ATT). This suggests that an average risk averse adopter would experience an unambiguous welfare gain through a combination of increased yield and reduced cost of risk bearing (See Di Falco & Chavas, 2009). Furthermore, SRI adoption would reduce the yield variability of a randomly picked farmer by nearly 30 percent (ATE). Meanwhile, an average non-adopter would experience an even larger decrease in variability by 75.8 percent should they adopt SRI (ATUT), although neither their expected yield nor skewness would be affected. Overall, these results point to positive and sizable treatment effects for an average farmer irrespective of their treatment status, with the average adopter standing to gain most.

These aggregate results, however, conceal considerable distributional effects among farmers. This is because, in the presence of substantial heterogeneity, farmers elect to adopt SRI not only on the basis of their observed characteristics but also based on private information about their anticipated benefits and costs of adoption (Bjrklund & Moffitt (1987)). Therefore, examining the average treatment effect of the marginal farmer (one who is at the margin of indifference between adopting and not adopting SRI) rather than average treatment effect of the average farmer may paint a different picture. We show that, far from being constant and homogenous, the marginal farmer's treatment effects decline in their unobserved, individual-specific resistance to treatment. Indeed, the marginal effects are typically high for farmers who are most inclined to adopt SRI since they reap an 83 percent return in yield and a 128 percent reduction in downside risk exposure that outweighs the 49 percent increase in yield variability. By contrast, farmers who are most resistant to adoption suffer a 66 percent yield loss, somewhat balanced by a 109 percent reduction in yield variability and no significant effect on downside risk exposure. These declining marginal treatment effects stand in sharp contrast to the constant average treatment effects on adopters (ATT) and average treatment effects on non-adopters (ATUT) presented above.

The results of this study improve our understanding of the behavioral and policy factors that can help explain constraints and opportunities in the adoption of new technology. This paper provides useful insights on the linkages between climate change perceptions and the yield risk impact of new technology in Africa. It suggests that sufficient awareness about climate change can contribute to increased yield and reduce exposure to downside risk, thereby improving food security. Given the potential for rural climate information to support adaptation and management of climate risk, there is a need to make climate information more accurate, accessible, and useful for farmers (Roncoli et al., 2002; Hansen, Baethgen, Osgood, Ceccato, & Ngugi, 2007). While the external validity of the study remains an open question considering the context-specificity of rainfed SRI, this study may still provide useful lessons to African farmers (beyond Tanzania), who, by and large, operate in rain-dependent environments.

One important shortcoming of the analysis is that it is based on a cross sectional survey, and thus many of the time-variant variables are only snapshots. Further, unmeasured characteristics that are important determinants of adoption and risk factors confound the observed covariates and the sign and magnitude of the resulting omitted variables bias is unknown. Future studies with panel data would enable controlling for the effect of such unobserved effects. Further, follow-up research could assess risk effects of the program by incorporating objective climate change measures (as opposed to climate change perceptions used in this paper), and the channels through which specific program effects materialize.

CRediT authorship contribution statement

Mare Sarr: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing, Supervision. **Mintewab Bezabih Ayele:** Conceptualization, Writing - original draft, Writing - review & editing. **Mumbi E. Kimani:** Methodology, Formal analysis, Writing - review & editing. **Remidius Ruhinduka:** Funding acquisition, Data curation, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A: Detail of the Marginal Treatment Effects U_D

Table 5
Marginal Treatment Effects as a function of U_D.

	(1)		(2)		(3)	
	Yield Baseline		Yield Variance		Yield Skewness	
Marginal Treatment Effects						
u_1	0.830^{***}	(0.183)	0.491^{*}	(0.272)	1.281^{*}	(0.773)
u_2	0.815^{***}	(0.180)	0.475^{*}	(0.265)	1.246^{*}	(0.752)
u_3	0.800^{***}	(0.177)	0.459^{*}	(0.257)	1.211^{*}	(0.732)
u_4	0.785^{***}	(0.174)	0.442^{*}	(0.249)	1.175^{*}	(0.711)
u_5	0.770^{***}	(0.172)	0.426^{*}	(0.242)	1.140^{*}	(0.691)
u_6	0.754^{***}	(0.169)	0.410^{*}	(0.234)	1.105^{*}	(0.671)
u_7	0.739^{***}	(0.167)	0.394^{*}	(0.227)	1.070	(0.651)
u_8	0.724^{***}	(0.164)	0.378^{*}	(0.219)	1.035	(0.630)
u_9	0.709^{***}	(0.162)	0.362^{*}	(0.212)	1.000	(0.610)
u_{10}	0.694^{***}	(0.160)	0.345^{*}	(0.204)	0.965	(0.590)
u_{11}	0.678^{***}	(0.157)	0.329^{*}	(0.197)	0.929	(0.570)
u_{12}	0.663^{***}	(0.155)	0.313^{*}	(0.189)	0.894	(0.551)
u_{13}	0.648^{***}	(0.154)	0.297	(0.182)	0.859	(0.531)
u_{14}	0.633^{***}	(0.152)	0.281	(0.175)	0.824	(0.511)
u_{15}	0.618^{***}	(0.150)	0.265	(0.168)	0.789	(0.492)
u_{16}	0.602^{***}	(0.149)	0.248	(0.161)	0.754	(0.472)
u_{17}	0.587^{***}	(0.147)	0.232	(0.154)	0.718	(0.453)
u_{18}	0.572^{***}	(0.146)	0.216	(0.147)	0.683	(0.434)
u_{19}	0.557^{***}	(0.145)	0.200	(0.140)	0.648	(0.416)
u_{20}	0.542^{***}	(0.144)	0.184	(0.133)	0.613	(0.397)
u_{21}	0.526^{***}	(0.143)	0.168	(0.127)	0.578	(0.379)
u_{22}	0.511^{***}	(0.142)	0.151	(0.121)	0.543	(0.361)
u_{23}	0.496^{***}	(0.142)	0.135	(0.115)	0.507	(0.344)
u_{24}	0.481^{***}	(0.141)	0.119	(0.109)	0.472	(0.327)
u_{25}	0.466^{***}	(0.141)	0.103	(0.103)	0.437	(0.311)
u_{26}	0.450^{***}	(0.141)	0.087	(0.098)	0.402	(0.295)
u_{27}	0.435^{***}	(0.141)	0.071	(0.093)	0.367	(0.280)
u_{28}	0.420^{***}	(0.141)	0.054	(0.089)	0.332	(0.266)

Table 5 (*continued*)

	(1)		(2)		(3)	
	Yield Baseline		Yield Variance		Yield Skewness	
u_{29}	0.405***	(0.141)	0.038	(0.085)	0.296	(0.252)
u_{30}	0.389***	(0.142)	0.022	(0.082)	0.261	(0.240)
u_{31}	0.374***	(0.143)	0.006	(0.080)	0.226	(0.230)
u_{32}	0.359**	(0.143)	−0.010	(0.078)	0.191	(0.221)
u_{33}	0.344**	(0.144)	−0.026	(0.077)	0.156	(0.213)
u_{34}	0.329**	(0.145)	−0.043	(0.077)	0.121	(0.208)
u_{35}	0.313**	(0.147)	−0.059	(0.078)	0.085	(0.204)
u_{36}	0.298**	(0.148)	−0.075	(0.079)	0.050	(0.203)
u_{37}	0.283*	(0.149)	−0.091	(0.081)	0.015	(0.204)
u_{38}	0.268*	(0.151)	−0.107	(0.084)	−0.020	(0.207)
u_{39}	0.253*	(0.153)	−0.123	(0.088)	−0.055	(0.212)
u_{40}	0.237	(0.155)	−0.140	(0.092)	−0.090	(0.220)
u_{41}	0.222	(0.157)	−0.156	(0.097)	−0.126	(0.229)
u_{42}	0.207	(0.159)	−0.172*	(0.102)	−0.161	(0.239)
u_{43}	0.192	(0.161)	−0.188*	(0.107)	−0.196	(0.251)
u_{44}	0.177	(0.163)	−0.204*	(0.113)	−0.231	(0.264)
u_{45}	0.161	(0.166)	−0.220*	(0.119)	−0.266	(0.278)
u_{46}	0.146	(0.168)	−0.237*	(0.125)	−0.301	(0.293)
u_{47}	0.131	(0.171)	−0.253*	(0.132)	−0.336	(0.309)
u_{48}	0.116	(0.173)	−0.269*	(0.138)	−0.372	(0.325)
u_{49}	0.101	(0.176)	−0.285**	(0.145)	−0.407	(0.342)
u_{50}	0.085	(0.179)	−0.301**	(0.152)	−0.442	(0.359)
u_{51}	0.070	(0.182)	−0.317**	(0.159)	−0.477	(0.377)
u_{52}	0.055	(0.185)	−0.334**	(0.166)	−0.512	(0.395)
u_{53}	0.040	(0.188)	−0.350**	(0.173)	−0.547	(0.414)
u_{54}	0.025	(0.191)	−0.366**	(0.180)	−0.583	(0.432)
u_{55}	0.009	(0.194)	−0.382**	(0.188)	−0.618	(0.451)
u_{56}	−0.006	(0.197)	−0.398**	(0.195)	−0.653	(0.470)
u_{57}	−0.021	(0.201)	−0.414**	(0.202)	−0.688	(0.490)
u_{58}	−0.036	(0.204)	−0.431**	(0.210)	−0.723	(0.509)
u_{59}	−0.051	(0.207)	−0.447**	(0.217)	−0.758	(0.529)
u_{60}	−0.067	(0.211)	−0.463**	(0.225)	−0.794	(0.548)
u_{61}	−0.082	(0.214)	−0.479**	(0.232)	−0.829	(0.568)
u_{62}	−0.097	(0.218)	−0.495**	(0.240)	−0.864	(0.588)
u_{63}	−0.112	(0.221)	−0.511**	(0.248)	−0.899	(0.608)
u_{64}	−0.127	(0.225)	−0.528**	(0.255)	−0.934	(0.628)
u_{65}	−0.143	(0.229)	−0.544**	(0.263)	−0.969	(0.648)
u_{66}	−0.158	(0.232)	−0.560**	(0.271)	−1.005	(0.669)
u_{67}	−0.173	(0.236)	−0.576**	(0.278)	−1.040	(0.689)
u_{68}	−0.188	(0.240)	−0.592**	(0.286)	−1.075	(0.709)
u_{69}	−0.203	(0.244)	−0.608**	(0.294)	−1.110	(0.730)
u_{70}	−0.219	(0.247)	−0.625**	(0.301)	−1.145	(0.750)
u_{71}	−0.234	(0.251)	−0.641**	(0.309)	−1.180	(0.771)
u_{72}	−0.249	(0.255)	−0.657**	(0.317)	−1.216	(0.791)
u_{73}	−0.264	(0.259)	−0.673**	(0.325)	−1.251	(0.812)
u_{74}	−0.280	(0.263)	−0.689**	(0.333)	−1.286	(0.832)
u_{75}	−0.295	(0.267)	−0.705**	(0.340)	−1.321	(0.853)
u_{76}	−0.310	(0.271)	−0.722**	(0.348)	−1.356	(0.874)
u_{77}	−0.325	(0.275)	−0.738**	(0.356)	−1.391	(0.894)
u_{78}	−0.340	(0.279)	−0.754**	(0.364)	−1.426	(0.915)
u_{79}	−0.356	(0.283)	−0.770**	(0.372)	−1.462	(0.936)
u_{80}	−0.371	(0.287)	−0.786**	(0.379)	−1.497	(0.957)
u_{81}	−0.386	(0.291)	−0.802**	(0.387)	−1.532	(0.977)
u_{82}	−0.401	(0.295)	−0.819**	(0.395)	−1.567	(0.998)
u_{83}	−0.416	(0.299)	−0.835**	(0.403)	−1.602	(1.019)
u_{84}	−0.432	(0.303)	−0.851**	(0.411)	−1.637	(1.040)
u_{85}	−0.447	(0.307)	−0.867**	(0.419)	−1.673	(1.061)
u_{86}	−0.462	(0.311)	−0.883**	(0.427)	−1.708	(1.082)
u_{87}	−0.477	(0.315)	−0.899**	(0.435)	−1.743	(1.103)
u_{88}	−0.492	(0.320)	−0.916**	(0.442)	−1.778	(1.123)
u_{89}	−0.508	(0.324)	−0.932**	(0.450)	−1.813	(1.144)
u_{90}	−0.523	(0.328)	−0.948**	(0.458)	−1.848	(1.165)
u_{91}	−0.538	(0.332)	−0.964**	(0.466)	−1.884	(1.186)
u_{92}	−0.553	(0.336)	−0.980**	(0.474)	−1.919	(1.207)
u_{93}	−0.568*	(0.341)	−0.996**	(0.482)	−1.954	(1.228)
u_{94}	−0.584*	(0.345)	−1.013**	(0.490)	−1.989	(1.249)
u_{95}	−0.599*	(0.349)	−1.029**	(0.498)	−2.024	(1.270)
u_{96}	−0.614*	(0.353)	−1.045**	(0.506)	−2.059	(1.291)
u_{97}	−0.629*	(0.358)	−1.061**	(0.514)	−2.095	(1.312)
u_{98}	−0.644*	(0.362)	−1.077**	(0.521)	−2.130	(1.333)
u_{99}	−0.660*	(0.366)	−1.093**	(0.529)	−2.165	(1.354)
Observations	305		305		305	
P-Value essential heterogeneity	0.001 ***		0.044 **		0.098*	

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