Does the Adoption of Weather Tolerant Variety Contribute to Reduction in Rice Yield Loss? Panel Data Survey from Chinese Rice Farmers

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Abstract: Climate extremes, characterized by droughts and floods, have become one of the major constraints to sustainable improvement of rice productivity. Variety choice, considered as one of the main adaptation measures, could help farmers reduce yield loss resulting from these extremes. Based on a three-year panel survey of 1,080 Chinese rice farms in major rice producing provinces, we study the effect of adopting weather tolerant variety rice as a main adaptation measure against climate extremes. Taking into account the endogeneity of adoption behavior, we employ an endogenous switching regression to separately estimate the treatment effects of adoption for adopters and non-adopters. We find that farmers who adopted the new variety increased yield by 537 kg/ha (about 7%), compared with the counterfactual case of no-adoption. In contrast, the farmers who did not adopt, would increase rice yield by 272 kg/ha (about 4 %) if they adopted, much smaller than the adopters. However, adoption of new variety demands more knowledge, better education, more intensive management, and higher seed costs. As a policy implication, expansion of public extension services could help relax these restrictions.

Key words: Climate extremes, rice, weather tolerant variety, yield

1. Introduction

Climate extremes, characterized by droughts and floods, have significant adverse effects on agricultural production (Liu and Chen，2000；Wang et al.，2007；Long et al.，2011) and have become a major challenge to sustainable development of agriculture (Stern, 2006；Mendelsohn and Dinar, 2009；De Salvo et al., 2013；Lin，1997；Pan, 2011；Chen, 2015). The frequency of the extremes is predicted to increase in the future and the challenge to agriculture and international food security has been pronounced (World Bank, 2013). The predictions show that total area suffering from drought globally will increase between 15~44% by the end of the twenty-first century (IPCC，2014). In China, the annual average crop area suffering from drought has more than doubled since the 1950s, and the frequency of flood events has also increased (MWR, 2014).The direct economic losses due to meteorological disaster amount to RMB100 billion each year，accounting for an estimated 3~6% of GDP, among of which drought is the most severe weather events faced by China's rice producers, followed by flood. Ju et al. (2007) report that the areas affected by drought and flood respectively account for 17.6% and 8.1% of the total grain acreage, while the proportions for each province respectively are about 5～19% and 2～10%; with the frequent occurrence of climate extremes, even if the irrigation condition can be satisfied under current technical level, the losses of wheat, corn and rice yields are expected to be 3~7%, 1~11% and 5~12%, respectively. Rice is the main staple food in China, which produces nearly 30% of the world's total rice output (FAOSTAT, 2014), but it is particularly vulnerable to climate extremes. Hence we especially shed light on rice production in this study.

Overcoming the challenge to food security caused by increasing weather and climate extremes has drawn much attention from researchers. Recent studies have identified a variety of effective adaptation measures being taken by farmers to cope with climate change, such as diversifying crop varieties (Bradshwa et al., 2004; Bryan et al., 2009；Chen et al.，2014; Bai et al. 2015), adjusting the timing of sowing and harvesting (Smit and Skinner, 2002; Challinor et al., 2007; Tubiello et al., 2007；Deressa et al., 2009), increasing input use and changing plant densities (Cuculeanu et al., 1999；Smit and Skinner, 2002; Meza et al., 2008；Seo and Mendelsohn, 2008), and reseeding, fixing or cleaning seedlings (Huang et al., 2015). However, most studies focused on the determinants of adaptation decisions, the effectiveness of adaptation practices has not been well evaluated. For example, Deressa et al. (2009) find that household characteristics and access to extensions influence farmers' adaptation decisions in Ethiopia. Similarly, Chen et al. (2014) indicate that farm characteristics and local government policies influence farmers' adaptation decisions in China. Though some studies have treated some farm management practices as adaptation measures and analyzed the impact of adaptation on crop yield (Yesuf et al., 2008; Di Falco et al., Veronesi, 2011; Pan, 2011; Chen, 2015), yet whether these adaptation measures can help mitigate the impact of climate extremes remains unclear.

Variety choice is a major adaptation strategy. In other words, farmers can adopt new variety with strong resistance to reduce risks from climate extremes (Selvaraj and Ramasamy, 2006). Given that the stress tolerant varieties are of shorter duration, and have ability to withstand high heat, drought, flood and other unfavorable weather conditions, crop breeding for weather-tolerance variety has attracted considerable research attention in the recent past (Lybbert and Bell, 2010; Bai et al. 2015). In the case of rice, it has been reported to have a yield advantage of 5-28% over the existing varieties (Virk and Witcombe, 2007; Pray et al., 2011; IRRI, 2013). The adoption of excellent variety with strong tolerance is a main adaptation measure of farmers, which can mitigate the harmful effects of climate change on rice (Wu, 2004; Wang, 2005). Besides, several studies have examined the factors affecting farmers' choice of seed varieties. Meng et al. (2005) indicated that yield potential is the top concern when farmers in Guangxi province make a decision of seed purchase, which could help maximize the profit. Yuan et al. (2009) found that farmers' maize seed choice behavior is heavily motivated by increasing high yield, other factors including labor, marketing, local cultivation knowledge, livelihood strategy and the awareness of risk and so on. Similarly, Cao (2011) indicated that yield potential is a major driver for adoption behavior in China, significantly related to labor force and the age of household head. These studies, however, did not make clear that to what extend farmers' adoption behavior is affected by climate change, particularly, the increasing climate extremes.

Given the increasing severity of climate extremes and the potential role of stress tolerant variety in mitigating climate risks, it is important to identify the factors influencing farmers' adoption of weather tolerant variety, and to evaluate whether their adoption can really reduce rice yield loss. The adoption of stress tolerant variety responds to extreme climate can be considered as an effective adaptation strategy to climate extremes, an issue which is only studied in a limited way in the current literature. Particularly, the adoption behavior could be endogenous, but it has not been well examined in the literature. Taking into account the endogeneity of adoption, we shed light on the impact of adoption of weather tolerant varieties on rice yield in China with use of a three-year panel dataset collected from 1,080 Chinese rice farmers in 4 major rice producing provinces in China: Zhejiang and Jiangsu in the coastal area of eastern China, Sichuan in southwest China, and Hunan in central China. We are particularly interested in identifying factors influencing farmers' adoption behavior and evaluating whether their adoptions can reduce rice yield loss. The nature of panel data enables us to compare the adoption behaviors in different years in respond to different weather situations, while controlling for unobserved heterogeneities. It is methodologically superior to the cross section analysis, prevalent in the literature (e.g. Wang et al. 2009; Wang et al. 2013).

Rest of the paper is organized as follows. Section 2 illustrates the empirical strategy which examines farmers' adoption of weather tolerant variety and its impact on rice production. Section 3 introduces the data and sampling method used in this study. Then Section 4 provides econometric estimation results. The final section concludes with policy implications.

2. Model Specification

2.1 Base Model

There are two broad streams of literature which models the impact of climate change on agricultural production. One stream is called Ricardian method, which implicitly takes into account all adaptation measures, observable or unobservable, in the impact analysis (e.g. Deschenes and Greenstone 2007; and Wang et al. 2009, 2013). One stream is called production approach, which explicitly incorporates adaptation to production process (e.g. Holst, Yu and Gruen 2013). The latter is more flexible, as it can analyze the direct impact of adaptations. Following Kim and Chavas (2003), Di Falco and Chavas (2009) and Holst, Yu and Gruen (2013), we take the production function approach with consideration of adaptation behavior, and specify the rice yield function as:

(1) $$\log(y) = f(A, X, \beta) + \mu$$

Where y is the rice yield (kg/ha); A is a dummy variable denoting the adoption of weather tolerant variety (1 for adoption, and 0 otherwise). X is a set of explanatory variables, including: a) farm characteristics including characteristics of household head (gender, education and years of experience), agricultural labor, soil quality by category (low, moderate, and high), and type of rice planted (single-seasoned and double-seasoned); b) production inputs (labor, land, fertilizer and pesticide, machinery and other inputs) specified in logarithm; c) year dummies for 2013 and 2014 to control for the effects related to time, such as technological change; and d) province dummies (fixed effects at the provincial level) to control for unobserved heterogeneities for province. β is a vector of parameters to be estimated. u is the error term that captures measure errors，unobserved heterogeneities, and uncertainties, and satisfies $E(u) = 0$.

If $f(A, X, \beta)$ is specified as a linear function, the coefficient of A exactly measures the impact of adoption of weather tolerant variety on rice output. However, the adoption behavior, which is linked to climate extremes, could be endogenous. The adopters and non-adopters may have different production functions, so that is not good to pool the two yield functions together. A separated estimation is necessary, and we proposed an endogenous switching regression to tackle this issue.

2.2 Modeling Adaptation to Climate Extremes

To deal with the endogeneity of farmers' adoption behavior (A), we further employ an endogenous switching regression model. In the switching regression approach, farmers are partitioned into two regimes according to the adoption decision (e.g., adopters and non-adopters). Theoretically, farmers typically choose to adopt when there is a net benefit from doing so (Abdulai and Huffman 2014; Bai et al. 2015). Farmer *i*'s adoption decision (whether to adopt weather tolerant variety) thus can be modelled by a latent variable explanatory variable A_i^*as

(2) $A_i^* = g(X, Z, D, \gamma) + \eta_i, \;\; A_i = 1[A_i^* > 0],$

Where the variable Z is an instrument variable (IV) for A. It is defined as access to the public service related to the extension and technical guidance for new rice variety or not at the village level (1 = yes, 0 otherwise). Furthermore, we control the level of climate extremes D, which includes three dummy variables: low climate extreme (1 = yes, 0 otherwise), moderate climate extreme (1=yes, 0 otherwise) and severe climate extreme (1=yes, 0 otherwise) measured at the county level.

Then, γ denotes a vector of parameters to be estimated. The error term η with mean zero and variance1 captures measurement errors and unobserved factors.

Given that the choice whether to adopt weather tolerant variety, separated outcome functions are specified for adopters and non-adopters:

(3a) Regime 1 (Adopters):

$$\log(y_{1i}) = f(A, X, D, \beta_1) + \varepsilon_{1i} \quad if\ A_i = 1,$$

(3b) Regime 2 (Non-adopters):

$$\log(y_{2i}) = f(A, X, D, \beta_2) + \varepsilon_{2i} \quad if\ A_i = 0$$

Where y_{1i} and y_{2i} are the outcome variables (rice yield in logarithm) for adopters and non-adopters, respectively. The vectors β_1 and β_2 are parameters to be estimated.

The three error terms η, ε1 , and ε2 in equations (2), (3*a*), and (3*b*) are assumed to have a trivariate normal distribution, with zero mean and the following covariance matrix:

$$\Sigma = \begin{bmatrix} 1 & \sigma_{\eta 1} & \sigma_{\eta 2} \\ \sigma_{1\eta} & \sigma_1^2 & \sigma_{12} \\ \sigma_{2\eta} & \sigma_{21} & \sigma_2^2 \end{bmatrix},$$

where $Var(\varepsilon_1)=\sigma_1^2$, $Var(\varepsilon_2)=\sigma_2^2$, $Var(\eta)=1$, $Cov(\varepsilon_1, \varepsilon 2) = \sigma 12$, $Cov(\varepsilon_1, \eta) = \sigma_{1\eta}$, and $Cov\ (\varepsilon_2\ , \eta) = \sigma_{2\eta}$. Note that since y_{1i} and y_{2i} are not observed simultaneously, so that it become a sample selection problem, and the covariance between $\varepsilon_1$and $\varepsilon_2$is not defined. The sample selection bias may lead to nonzero covariance between the error term of the selection equation (2) and the outcome equation (3) (Maddala, 1983). According to Lee and Trost (1978), the expected values of the error terms ε1 and ε2, conditional on the sample selection are given as:

(4) $E[\varepsilon_{1i}|A_i = 1]$

$=E\ (\varepsilon_{1i}|\ \eta > -g\ (X, Z, D, \gamma)$

$=\sigma_{1\eta}\frac{\varphi[g(X,Z,D,\gamma)/\sigma]}{\Phi[g(X,Z,D,\gamma)/\sigma]} = \sigma_{1\eta}\lambda_{1i},$

And

(5) $E[\varepsilon_{1i}|A_i = 0]$

$=E\ (\varepsilon_{2i}|\ \eta \leq -g\ (X, Z, D, \gamma)$

$=-\sigma_{2\eta}\frac{\varphi[g(X,Z,D,\gamma)/\sigma]}{1-\Phi[g(X,Z,D,\gamma)/\sigma]} = \sigma_{2\eta}\lambda_{2i},$

Where $\varphi(\cdot)$ is the standard normal probability density function, and $\Phi(\cdot)$ is the standard cumulative distribution function. The terms λ_1 and λ_2 refer to the inverse Mills ratios evaluated at $g(X, Z, D, \gamma)$, and are incorporated into equations (3a) and (3b) to account for sample selection bias. Together with the probit model of selection in Equation (2), the endogenous switching regression can be estimated by the full information maximum likelihood (FIML) method (Lokshin and Sajaia, 2004), though the computation requirement is very intensive.

To account for the possible heterogeneity in farmers' decisions on whether to adopt or not, we first included the dummy variable of rice type (double-seasoned rice) to capture the specificity of the different crops. Second, we used the White sandwich estimator for robust standard errors (Shen and Hartarska, 2013). This approach yields consistent estimates of the covariance matrix without making distributional assumptions (Freedman, 2006).

2.3 Estimation of adoption effects

The impact of weather tolerant rice adoption on yield can be examined by first specifying the expected values of the outcome. For an adopter and a non-adopter of the new variety, the expected value of the outcomes are calculated, respectively, as

(6) $E[y_{1i}|A_i = 1] = f(A, X, D, \beta_1) + \sigma_{1\eta}\lambda_{1i}$

and

(7) $E[y_{2i}|A_i = 0] = f(A, X, D, \beta_2) + \sigma_{2\eta}\lambda_{2i}$.

In order to estimate the treatment effect, we have to estimate the counterfactual effects. Accordingly, the expected values of the same adopter, had he chosen not to adopt weather tolerant variety, and of the same non-adopter, had he chosen to adopt stress tolerant variety are given, respectively, as

(8) $E[y_{2i}|A_i = 1] = f(A, X, D, \beta_2) + \sigma_{2\eta}\lambda_{1i}$

and

(9) $E[y_{1i}|A_i = 0] = f(A, X, D, \beta_1) + \sigma_{1\eta}\lambda_{2i}$.

The changes in outcomes due to the adoption of weather tolerant variety can then be specified as the difference between adopters and non-adopters (Di Falco, Veronesi, and Yesuf 2011). The average treatment effect for the treated (ATT) is represented by the difference between (6) and (8):

(10)
$$\begin{aligned} \text{ATT} &= E[y_{1i}|A_i = 1] - E[y_{2i}|A_i = 1] \\ &= f(A, X, D, \beta_1) - f(A, X, D, \beta_2) \\ &\quad +(\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i} \, . \end{aligned}$$

Similarly, the average treatment effect for the untreated (ATU) that did not adopt can be calculated as the difference between (9) and (7):

(11)
$$\begin{aligned} \text{ATU} &= E[y_{1i}|A_i = 0] - E[y_{2i}|A_i = 0] \\ &= f(A, X, D, \beta_1) - f(A, X, D, \beta_2) \\ &\quad +(\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i} \, . \end{aligned}$$

Such a procedure taking into account the selection bias ($\lambda 1$, $\lambda 2$), could yield better treatment effects. ATT can be explained as the effect of adoption for those adopters, while ATU is the possible effect of adoption if those non-adopters adopted the new variety. A comparison between ATT and ATU could provide a good benchmark for explaining the non-adoption behavior.

3. **Data and Sampling Methods**

We use a stratified sampling method to select rice farms in order to make the samples more representative. Rice in China is mainly planted in the Northeast Plain, the Yangtze River basin and Southeast coastal area, respectively accounting for 12%, 64%, and 22% of the national cultivating area. Heilongjiang in the Northeast region; Hunan, Hubei, Jiangxi in the Central region; Jiangsu, Zhejiang, Anhui, Guangxi, Guangdong in East region and Sichuan, Yunnan in Southwest region are the eleven major provinces of rice production, together accounting for over 80 percent of the national total production (NBSC, 2015). Climate change has impact on these major rice production areas at various degrees. For instance, the potential rice output in Northeast China may increase due to global warming, but the yields in other three major regions might be adversely affected (Tang et al. 2000). Therefore, taking full consideration of regional crop production systems and climate situations, we selected four provinces from the three major regions with high risk of rice yield loss: Zhejiang and Jiangsu in the coastal area of eastern China, Sichuan in southwest China, and Hunan in central China. We then conducted a large-scale household survey regarding the impact of adaptation to climate change on rice production during the period from October 2014 to May 2015.

We then selected 6 counties from each province according to the following three standards. First, we identified all counties that had experienced climate extremes over the period of 2012–2014. According to China's national standard for natural disasters (CMA，2004), the severity of climate extremes has three categories: low (10~30% of yield loss), moderate (30~50％ of yield loss) and severe (greater than 50% of yield loss). Second, from the counties identified in the first step, we only kept those which also had experienced a "normal year" in these three years. Finally, we randomly selected 6 counties from the listed counties identified in the last two steps. This sampling approach allowed us to examine differences between normal years and years with climate extremes.

Within each of the 24 selected counties, all townships were divided into three groups based on the condition of agricultural production infrastructure, and one township was randomly selected from each group. The same sampling techniques were applied to select three villages from each township. Finally, 15 households were randomly selected from each selected village for face-to-face interviews. A total of 1,080 from 72 villages in 24 counties rice farms were interviewed. Excluding the incomplete samples，the final sample used in our analysis includes 1,057 households from 68 villages in 24 counties (see Table 1).

Considering that most farms in our sample both planted single-seasoned rice and double-seasoned rice, we analyzed data by rice types: single-seasoned rice and double-seasoned rice. We thus arrive at the final number of 3,171 observations for rice production. For each observation, we collected data for a normal year and a year with climate extremes within the period of 2012–2014. The information collected in the survey include: 1) characteristics of households and farms; 2) detailed rice production cost information (e.g., land, labor, fertilizer and pesticide, machinery service, other inputs); 3) rice yield, soil quality and rice type; 4) farmers' adoption behavior for weather-tolerant variety in both years; and 5) availability of public services related to the extension and technical guidance for new rice variety which was collected in the village level survey.

Table 2 provides a description statistics for variables included in the empirical models. Of the 1057 farms，most of household heads are male-dominated and relatively low-level educated (middle school or below), but have rich rice production experiences (an average of 20 years). Each farm on average has 2 agricultural labor forces.

[Insert Table 1 &2 here]

The average rice yield is 7,935 kg/ha, slightly higher than the 2014 national average rice yield, which is 7,274 kg/ ha[1]. The average cost of labor, land, chemical fertilizers and pesticides, mechanical service and other inputs is approximately RMB 7,895, RMB 4,369, RMB 3,585, RMB 2,443 and RMB 1,178 per ha, respectively. Particularly, labor cost and land cost are the highest, consistent with the clear upward trend of the two costs in recent years. However, only one-fourth of rice farms in our study can access to the public service related to the extension and technical guidance for new rice variety at village level, suggesting that the current public services are generally low and there is still much room to improve.

4. Estimation Results and Discussion

4.1 Joint Estimation of Selection Function and Rice Yield Function

[1] Source: Table 1-2-1, Rice Production Costs and Revenues. *Collections of National Agricultural Production Costs and Revenues* (2015) (Quan guo nong chan pin cheng ben shou yi zi liao hui bian 2015).

As aforementioned, equations (2), (3*a*), and (3*b*) can be jointly estimated by the maximum likelihood method, and the results are reported in Table 3. The first column reports the estimation results for the selection function (2), which is a probit model helping explain why some farmers adopt weather tolerant variety and others not. The second and third columns present, respectively, the estimated coefficients of rice yield functions (3*a*) and (3*b*) respectively for farmers who adopted weather tolerant variety and who did not. Most of the coefficients are consistent with our expectations and the current literature (e.g., Huang et al. 2008; Holst et al. 2013； Huang et al. 2015; Bai et al. 2013).

[Insert Table 3 here]

4.2 Results of Selection Function

In the results of selection Function (2), we are particularly interested in the effects of different severity of extreme climate on farmers' adoption decision. Though some previous studies (e.g. Di Falco, Veronesi, and Yesuf, 2011) did not find strong relationship between climate change variables and farmers' adaptation decisions, we have different evidence. The coefficients for low, moderate and severe climate extremes are 0.390, 0.756, and 0.939, and all statistically significant. It is consistent to our common sense that rice farmers are more likely to adopt stress tolerant variety when they have experience of suffering from more serious climate extremes.

Household characteristics could affect the adoption behavior. Both the education of household heads and agricultural labor forces have significant and positive effects on the probability of adopting the new variety. This result confirms that households headed by high educated people and more agricultural labor forces tend to adopt the new variety. It is interesting that the variable of household head experience in agriculture is statistically significant. Its value is -.015, and implies that more years of experience in rice production are less likely to adopt the new variety. It is possible that the new variety demands new knowledge for planting, while the experience accumulated from the old variety may not work. According to the estimation results, gender of household head does not play significant roles in adoption behavior.

The estimated coefficients for moderate soil quality and high soil quality are -0.360 and -0.621, and both statistically significant. It shows that soil quality is negatively correlated with the adoption probability. It is understandable that better soil quality and more favorable growing conditions could make rice less vulnerable to climate extremes, so that farmers have lower motivation to adopt stress tolerant variety, which is usually more expensive.

The coefficients for the year dummies of 2013 and 2014 are statistically significant, and the values respectively are 0.042 and 0.053, which indicates an increasing likelihood of adoption behavior.

Finally, we take the estimated coefficient for the instrument variable (IV) —local access to public services on new rice variety. As an instrumental variable, it should be correlated with selection behavior, but not the error terms in the output function. The estimated value is 0.360 and statistically significant at 1%. It implies that the IV is not a weak instrument. The coefficient also implies that local access to public services on new rice variety could help increase the likelihood of farmer adoption.

4.3 Estimation of Yield Functions

Equations (3a) and (3b) respectively show yield functions of adopters and non-adopters, as we assume that their technologies might be different.

First, we find that the severity of climate extremes in general decrease the rice outputs no matter for conventional variety or for weather tolerant variety. An exception is found for adopters in the severe extreme climate year: the estimated coefficient (-0.035) is statistically significant, but lower than that in moderate climate year (-0.068), suggesting that rice yield suffer more losses in moderate extreme climate year. This may be because the effect of stress tolerant rice varieties' resistance to extreme climate is limited due to the constraints on rice production technology and agricultural production infrastructure. However, comparing the coefficients between adopters and non-adopters under the same severity of climate extremes, the magnitudes in terms of absolute value for adopters are much smaller. It implies that the stress tolerant variety could help farmers reduce the yield loss resulting from climate extremes, given the same severity of climate extremes.

Second, there are only two input variables which are significant: land, fertilizer and pesticide for adopters. Particularly, adopters are found a significantly negative impact of land on output. The negative impact of land input suggests the average yield is negatively correlated with farm size, indicating a decreasing return to scale, a finding similar to that of many existing studies (e.g., Abdulla and Huffman 2014;Huang et al. 2015).

The point estimates for all input variables are generally small in the yield function. It implies that the yield of Chinese rice has reached a limit. Further increasing inputs do not help increase yield substantially, and future increase of rice output in China depends on the expansion of land, which is now limited in China. Having less significant coefficients for input variables is consistent with previous findings on intensive or excessive use of production inputs in China (e.g., Huang et al. 2008; Holst, Yu, and Grunt 2013).

Third, the estimated coefficient for male head of households is negative and statistically significant, suggesting that women, which are more risk averse, tend to be more motivated to adopt stress tolerant variety to minimize the yield loss caused by extreme climate. The positive impact of agricultural labor force suggests that more agricultural labor forces is beneficial for increasing rice yield， as rice production demand more labor inputs (e.g., Abdulla and Huffman, 2014).

Finally, for non-adopters, the estimated coefficient for double-seasoned rice is negative and statistically significant, suggesting that the yield of double-seasoned rice is significantly lower than single-seasoned rice, this may be mainly determined by rice's labor-intensive characteristics, and shorter growing season. Single-seasoned rice farmers could spend more time and effort on rice cultivation and farm management and this intensive cultivation helps improve rice yield. Surprisingly, other variables such as the education of household head and soil quality are not statistically significant, which is contrary to the conclusion that highly educated people and better soil quality positively impact rice yield (Wang et al., 2014).This may be due to the fact that China has built up a good agricultural extension system, in which individual heterogeneities of rice production skills become less important. .

4.4 Effects of adoption on Rice Output

The estimates for the average treatments effect (ATT and ATU) on the mean of rice yield are presented in table 4. Obviously, the results reveal that the adoption of stress tolerant variety could significantly increases rice yield (or reduce the loss), even the severity of climate extremes are controlled in the regression. Specifically, in the counterfactual case represented by equation (8), farmers who adopted would reduce rice yield by 537kg/ha (about 7%) if they had not adapted (row 1). In the counterfactual case of equation (9), for farmers who did not adopt, they would increase rice yield by 272 kg/ha (about 4 %) if they adopted (row 2). These findings suggest adapting to extreme climate through adopting stress tolerant variety does increase rice production and contribute to the reduction in rice yield loss.

[Insert Table 4 here]

It also explains why some farmers do not adopt the weather tolerant variety. The possible benefit for non-adopters, if they had adopted the new variety, is much smaller than those adopters. Adoption of new variety demands new knowledge, intensive management, and higher seed cost, and the benefit might not overcome the learning costs (Yu and Zhao 2009). Further expansion of the weather tolerant rice variety calls for more government action on extension services.

5. Conclusions

Using a panel data survey from 1,080 rice farmers conducted in four provinces in China, this article investigates the contribution of adopting weather tolerant variety in response to extreme climate to the rice yield loss reduction (or yield increase). Different from the current literature, we take into account the endogeneity of adoption behavior, and employ an endogenous switching regression to separately estimate the treatment effects of adoption for adopters and non-adopters.

The results of adoption behaviors reveals that farmers adoption decision of weather tolerant rice variety mainly depends on the severity of climate extremes, local access to public service on new variety, the education of household heads, agricultural labor forces and famers experience on rice production. The former four factors could incentivize farmers to adopt the new variety, while more experience on rice production discourage farmers to adopt, perhaps due to high learning costs.

We assume that rice productions for adopters and non-adopters have different technologies in the endogenous switching regression. Specifically, farmers who adopted the new variety increased yield by 537 kg/ha (about 7%), compared with the counterfactual case, in which if they had not adopted. In contrast, the farmers who did not adopt, would increase rice yield by 272 kg/ha (about 4 %) if they adopted. In both equations, the severity of climate extremes is controlled. It suggests that adopting stress tolerant variety could generally increase rice production and contribute to the reduction in rice yield loss.

It also indicates that the possible benefit of adopting weather tolerant variety for non-adopters is much smaller than those adopters. Adoption of new variety demands new knowledge, high education, more agricultural labor forces, and more seed costs and the benefit might not overcome the learning costs and adoption costs. Further expansion of the weather tolerant rice variety calls for more government action on extension services.

In addition, we find that the output elasticities for all physical inputs are very small, except for land, fertilizer and pesticide. It implies that further increases of these inputs would have very small effect on expansion of rice output. Rice output mainly depends on land expansion, which is however now very limited in China.

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Table 1 Distribution of Surveyed Rice Farms

Province	County (No.)	Village (No.)	Household (No.)	Percentage (%)
Hunan	6	12	185	17.51
Jiangsu	6	15	225	21.28
Zhejiang	6	20	298	28.19
Sichuan	6	21	349	33.02
Total	24	68	1,057	100

Table 2 Descriptive Statistics of the Sample （N=1057）

Variables	Definition/Unit	Min	Max	Mean	Std.
Rice yield	kg / ha	4,664	11,595	7,935.52	1,678.60
Household Characteristics					
Gender	1=male；0=female	0	1	0.81	0.39
Education of household head	Years	0	19	7.68	2.38
Year of Experience in agriculture	Years	1	65	20.02	13.33
Family and Farm Characteristics					
Agricultural labor	No.	1	12	2.12	0.95
Soil quality	1=high quality ；2=moderate；3=low	1	3	1.90	0.39
Rice type	1=single-seasoned ；2=double-seasoned	1	2	1.25	0.45
Various inputs					
Labor	yuan/ha	776	14,925	7,895.05	3,209.59
Land	yuan/ha	1,050	22,500	4,368.60	2,149.50
Fertilizer and pesticide	yuan/ha	2,100	5,220	3,585	626
Machinery	yuan/ha	418	4,254	2,443	820
Other inputs	yuan/ha	132	1,693.24	1,178.35	237.57
Instrument variable					
Access to public service on new rice variety	1=yes；0=no	0	1	0.25	0.49

Table 3 Estimations of Farmer's Adoption on Stress Tolerant Variety and Its Impact on Rice Yield

	Adoption Choice (Adopter=1)	Rice yield (log)	
		Adopters	Non-adopters
Severe Extreme Climate			
Low	0.390***	-.017	-.552***
	(0.077)	(.097)	(.021)
Moderate	0.756***	-.068***	-.745***
	(0.252)	(.020)	(.022)
Severe	0.939***	-.035***	-1.068***
	(0.342)	(.012)	(.082)
Inputs			
Labor (log)		.089	-.051
		(.064)	(.053)
Land (log)		-.107***	-.158
		(.026)	(.106)
Fertilizer and pesticide (log)		.047***	.055
		(.013)	(.488)
Machinery (log)		.027	.040
		(.125)	(.048)
Other inputs (log)		.003	-.036
		(.065)	(.072)
Farm characteristics			
Gender	-.095	-.056***	-.046
	(.094)	(.018)	(.062)
Education	.170***	.004	.005
	(.043)	(.006)	(.024)
Years of experience in agriculture	-.015***	-.003	.001
	(.003)	(.002)	(.001)
Agricultural labor	.082***	.009***	.014
	(.031)	(.003)	(.012)
Moderate soil quality	-.360*	-.011	-.118
	(.221)	(.041)	(.091)
High soil quality	-.621***	-.010	-.095
	(.241)	(.039)	(.066)
Double-seasoned rice	.252	-.005	-.027***
	(.244)	(.036)	(.008)
D2013	.042***	.092**	.085***
	(.015)	(.046)	(.024)
D2014	.053**	.102**	.054

	(.024)	(.045)	(.048)
Instrument variable			
Access to public services on new rice variety	.360*** (.115)		
Constant	-1.034	3.901***	4.302***
	(.766)	(0.344)	(1.498)
Province dummies	Yes	Yes	Yes
rho_1		.400***	0.416***
		(.042)	(0.035)
rho_2		.845	-.761
		(.768)	(.635)

Notes: (1) Robust standard errors are reported in parentheses.

(2) *, **, and *** denote significance at the 10%, 5%, and1% levels, respectively.

(3) The sample consists of 3,171 observations (1,057×3years).

Table 4 Impacts of Adopting Stress Tolerant Variety on Rice Yield

Sub-samples	Decision stage		Treatment effects
	To adopt	Not to adopt	
Average expected rice yield (kg/ha)			
Rice yield for adopters (ATT)	8,041	7,504	ATT= 537***
Rice yield for non-adopters (ATU)	7,902	7,630	ATU= 272***

Note: ATT represents the effect of the treatment (i.e., adoption) on the treated (i.e., farmers that adopted stress tolerant variety), while ATU represents the effect of the treatment (i.e., adoption) on the untreated (i.e., farmers that did not adopt stress tolerant variety). Asterisks*** denote significance at the 1% level.