Farmer's Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China

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Abstract:

We explore how rice farmers adjust their farm management practices in response to extreme weather events and determine whether their adjustments affect the mean, risk and downside risk of rice yield. Based on a unique data from a survey of 1653 rice farmers in China, our econometric analyses show that the severity of drought and flood in the study areas significantly increases both the risk and downside risk of rice yield. The adopted farm management measures do respond to the serious drought and flood and can be considered as adaptation to climate change, an issue often been ignored in the previous studies. Then we model adaptation and its impact on rice yield on adopters and nonadopters. Based on a moment-based approach, we show that the adaptation through farm management measures significantly increases rice yield and reduces risk and downside risk of rice yield. The article concludes with policy implications.

Key words: adaptation, rice, China, extreme weather, yield, risk exposure

Farmer's Adaptation to Extreme Weather Events through Farm Management and Its Impacts on the Mean and Risk of Rice Yield in China

With the increasingly serious challenge of extreme weather events, how to adapt to the challenge has addressed great attention (Howden et al., 2007; IPCC 2014). The international community has called for incorporating climate change adaptation into national development plans (IPCC 2014; World Bank 2010). This is especially urgent for developing country farmers who are expected to bear the brunt of climate variability impacts (Seo and Mendelsohn 2008). In China, a national program to adapt to climate change was issued at the end of 2013, which highlights the adaptation strategy in agriculture and farmers' adaptive capacity building.

While a large body of literature on the farmer's adaptation to climate change has emerged (Chen, et al. 2014; Deressa et al. 2009; Seo and Mendelsohn 2008), little study has been undertaken to assess the effectiveness of farm management and other adaptation practices. Exceptions include Yesuf et al. (2008) and Di Falco et al. (2011). These studies treated farmers' adoptions as adaptation measures and analyzed the impact of adaptation on crop yield. Much studies have also analyzed agricultural risk, including the mean-variance investigation of input effects (e.g. Abedullah and Pandey 2004; Just and Pope 1979) and technology adoption (Foudi and Erdlenbruch 2012). However, it remains unclear that whether these adoptions lead to mitigation of the impact of extreme weather events.

Importantly, the influence of adaptation on downside risk exposure (e.g. on the probability of crop failure) remains poorly understood. In general, downside risk is the risk located in the lower tail of the payoff distribution (Kim et al. 2014). While useful information about the risk effects of input adjustments can be obtained from understanding their impact on yield variance, analyzing the variance effect alone would not enable one to distinguish between unexpected bad and good events (Di Falco and Veronesi 2012). Under the rising risks associated with climate variability, this has motivated research on the role of downside risk in risk management in crop production (Kim and Chavas 2003).

Given the severity of extreme weather events and the potential role of farm management in mitigating risks, several questions are raised. What are major farm management measures that are related to climate change and have been adopted by farmers? To what extent can these measures be considered as farmer's adaptation to climate variability? Are there adaptation measures can lead to a win-win benefit by lowering crop yield risks and also increasing the mean yield? Answers to these questions are critical not only for a better understanding of farmer's adaptation to extreme weather events, but also for providing empirical evidence for policy makers in the formulation of their climate change adaptation plan and investment.

The overall goals of this study are to explore how rice farmers adjust their farm management practices to extreme weather events and to determine whether their adjustments reduce rice yield loss and risk as well as downside risk in China. Rice is the main food staple in China that produced nearly 30% of rice in the world in recent years (FAOSTAT, 2011). The rice production loss due to drought and flood has been rising over time (NBSC 2012). To the best of our knowledge, there is no empirical study that has investigated how farm management adjusted to extreme weather events and its effects on both the mean and risk of rice yield in China and the rest Asian counties.[1] To limit the scope of this study, for the extreme weathers, we focus on drought and flood events only because they are the most serious weather events faced

[1] Until now, according to our knowledge, Di Falco and Veronesi (2012) is the only economic study that attempts to formally measure the impact of farmers' adaptation to climate change on downside yield risk in Ethiopia.

in rice production in China.

To achieve the above goals, we have the following three specific objectives. The first is to gain a better understanding on the extreme weather events (drought and flood) in rice production and farmer's responses to these events through adjusting their farm management practices. The second objective of this article is to identify whether the adoption of farm management measures is actually also responded to extreme weather events. Previous empirical studies on adaptation issues generally fail to do so. The third objective is to empirically examine the effects of the major farm management measures, which have been identified as adaptation to extreme weather events, on the mean, risk and downside risk (skewness) of rice yield. We approximate downside risk exposure by the third moment of the crop yield distribution. An increase in the skewness of yields means a reduction in downside risk (i.e., a decrease in the probability of crop failure) (Di Falco and Chavas 2009).

We model adaptation as a selection process and estimate a simultaneous equations model with endogenous switching to account for the heterogeneity in the decision to adapt or not, and to capture the differential impact of adaptation on adopters and nonadopters. Our results indicate that reseeding and fixing/cleaning seedlings are the major farm management practice adapted by rice farmers in response to extreme weather events. These farm management measures contribute to a significant reduction in risk and downside risk of yield. This implies that farmer's adaptation at the early stage of rice production is important risk management measure. The findings of this study have implications to the national adaptation plan and farmer's capacity building program in developing countries.

The rest of the article proceeds as follows. In the next section, we introduce the data that are used in this study. The following section illustrates the occurrence of extreme weather events and farmer's responses in the studied areas. After explaining the conceptual framework for examining the impact of adaptation, we present the results on the farm management measures adapted to extreme weather events and their impact on rice yield, focusing on the effects on mean, variance as well as skewness (or downside risk) of rice yield. The final section concludes.

Data and Sampling Methods

Except the secondary data on drought and flood discussed in the next section are from official report, all other data used in this study is a subset of data from a large-scale household survey on impact of and adaptation to climate change in crop production conducted in China in the end of 2012 and the early 2013. Based on regional crop production systems and climate situations, the survey covered nine provinces ranged from Jilin in the Northeast China to Hebei in the North China, Henan in the Central China, Shandong and Jiangsu in the coastal area of the Eastern China, Anhui and Jiangxi in the inland area of the Eastern China, Yunnan in Southwest China, and Guangdong in the South China. Of which, five provinces surveyed have households that produced rice in 2010-2012. While these five provinces may not fully represent China's rice production, they cover double-season dominated indica rice (early rice and late rice) production region (Guandong and Jiangxi), single-season dominated indica rice (middle rice) production region (Yunnan), single-season indica and japonic mixed rice (middle rice) region (Henan), and single-season japonica rice (middle rice) production region (Jiangsu).

Within each province, we followed three steps to select a set of counties that are considered to be a nature experiment on the extreme weather shocks. First, we selected all counties that had experienced the most serious drought or flood in one of the past three years (2010-2012). According to China' national standard for natural disaster, the serious of drought or flood is divided into four categories: most serious, serious, moderate and small. Second, based on the list of counties identified in the step one, we kept only the counties that also experienced a “normal year” in one of the past three years. However, the normal year here is a relative term because crop production often faces various weather shocks during its growing season in any year. It is better interpreted as a year with “average” weather situation in the long run and the shocks from the weather is no more than the moderate (the level 3 of natural disaster). The last, from the list of counties identified in the step two, three counties in each province except for Jiangxi (10 counties) and Guangdong (6 counties) were randomly selected for study.[2] This sampling approach allows us to examine differences in the two distinct years (“serious disaster year” and “relatively normal year”, from now on we use these two terms for easy of discussion) on farmers’ responses to the extreme weather events and the impacts of extreme weather events at farm level. At end, we have a sample of 25 counties.

Townships and villages were further selected before we sampled the households for interviews. Within each of 25 counties selected, all townships were ranged by conditions of agricultural production infrastructure and divided into three groups. One township was randomly selected from each group. The same approach was used to select three villages from each township. Last, we randomly selected 10 households for face-to-face interview in each sampled village. A total of 2250 households were identified in the five studied provinces. In each household, two plots with grain production were randomly selected and thus we have 4500 plots.

While a total of 2250 households were interviewed, some households did not plant rice or only one plot was planted for rice, the final sample used in our analysis

[2] Jiangxi and Guangdong had more counties included because we had funding from three projects in these two provinces that allowed us to expand our survey samples.

includes 1653 households with rice production and 2571 plots from 185 villages in 63 townships of 23 counties in five provinces. Because farmers in our samples also planted double-season rice (early and late season rice), we analyze data by type of rice: early season rice, middle season rice (or single-season rice), and later season rice. At end, we have a total of 3754 observations[3]. For each observation in each plot, we collected data in two time periods, the serious disaster year and the relatively normal year in 2010-2012. The time (or year) differs among counties.

While the survey covers a wide range of information, our analysis uses only the following data: 1) the characteristic of households and farm; 2) detailed plot level rice production data, especially production input (e.g., land, labor, fertilizer, machinery, crop varieties, pesticide, and others) and outputs in both serious disaster year and relatively normal year, and soil quality; 3) farmer's farm management measures that may relate to adaptations to the extreme weather events (e.g., drought or flood events) at plot level; and 4) availability of government service at villages on fighting extreme weather events, which was collected from the village level survey.

Extreme Weather Events and Rice Farmer's Responses

Overall, the frequency of extreme weather events such as drought and flood in studied provinces has showed a rising trend. Specifically, drought in Henan and Yunnan has become more serious, especially in Yunnan that has witnessed a number of extreme drought shocks in recent years. The average annual crop area suffering from drought in Yunnan increased from 0.47 million ha in the 1980s to 0.95 million ha in the 2000s, with an average growth rate of 3.2% (NBSC 2012). On the other hand, the other three provinces, Jiangxi, Guangdong and Jiangsu, have suffered more flooding problem though the drought were also often presented (NBSC 2012).

[3] The number of observations is 1349 for early rice, 950 for middle rice, and 1455 for late rice.

The household surveys also demonstrate the severity of the drought and flood reported by farmers in the study areas. For example, as shown in table 1, percentage of samples suffered from drought reached 41% in the serious disaster year (column 1). As expected, much less frequency (16%) of drought occurred in relatively normal year (column 2). Likewise, the percentage of samples affected by flood increased from16% in relatively normal year to 34% in serious disaster year (row 5). In both cases of drought and flood, the most frequency of disaster occurred in middle rice (60% for drought and 54% for flood) in serious disaster year (column 1). Interestingly, yield losses were quite similar when rice production faced the drought (23% to 24%) or flood (25% to 24%) in either serious disaster or relatively normal year (columns 3 and 4). Because these results were reported by farmers, the numbers presented in table 1 obviously already accounted for farmer's response to drought and flood.

In response to the rising trend of extreme weather events, farmers may take different measures, including physical and non-physical measures. This study specifically focuses on the non-physical measures such as farm management measures as they usually are the most convenient ones that farmers can access during crop growing season. Based on field survey, the most frequent farm management measures used by farmers related to drought and flood are reseeding, fixing and cleaning seedlings. On the average, 30% of samples used these measures (table 2). They are crucial at the early stage of rice production when facing drought or flood. Importantly, the field surveys also revealed that the adoption rate of the above farm management measures was generally higher in serious disaster year (33%) than that in relatively normal year (26%). While we are not sure to what extent of adopting farm management measures was response to the drought and flood, we argue that, the differences in adoption of farm management measures between the serious disaster year and the relatively normal year must largely belong to farmer's adaptation to the more serious drought or flood. For example, the increment of 7% (33-26) of the adoption of reseeding, fixing and cleaning seedlings represents the adaptation to deal with the extreme weather events. Meantime, farmers also adopted other farm management measures such as changing the rice varieties in the next season and adjusting fertilize use (table 2). But the difference between the serious disaster year and the relatively normal year was not significant.

Recent studies on determinants of adaptation have identified many factors that affect farmers' adaptation decisions to climate change. For example, based on a survey in Ethiopia, Deressa et al. (2009) found that the characteristics of household and access to extension influence farmer's adaptation decisions. The empirical studies in China found that, in addition to farm characteristics, local government policy support against drought and access to government's technical service against drought also have significant effects on farmer's adaptation (Chen et al. 2014; Wang et al. 2014). In this study, we also consider these factors when we develop the empirical model to examine farmer's adaptation behaviors and the effectiveness of the adaptations in reducing the risk of extreme weather events. For farm management measures, we focus on the most common measures that are used by farmers in our study areas: reseeding, fixing and cleaning seedlings. For easy of discussion, we still call these as farm management measures in the rest of this article.

Modeling and Estimation Procedure

We want to evaluate the impacts of farmer's adaptation to the extreme weather events through adjusting farm management practices on the mean yield, risk and downside risk of rice yield. To do this, we start with a moment-based approach (see Antle 1983), the first three sample moments of the production distribution of each farmer, namely the mean, risk (or variance), and downside risk (skewness) of rice yield, are estimated. Then, we incorporate the estimated three moments in an econometric model respectively as independent variables, and analyze how farmer's adaptation affects the above three outcomes.

Econometric Model of Mean Yield, Risk and Downside Risk

Following Antle (1983) and Antle and Goodger (1984), we rely on a moment-based approach that allows a flexible representation of the production risk, which has been widely used in agricultural economics to model the implications of weather risk and risk management (Kim and Chavas 2003; Koundouri et al. 2006; and Di Falco and Chavas 2009). In our study, the rice yield function in log (y) under production uncertainty can be defined as:

(1) $y = f_1(A, x, \theta_1) + u$

where A is adaptation with a value of 1 if a farmer adopts the farm management measures and 0 otherwise. x is a set of explanatory variables that include: a) production inputs (labor, fertilizer, machinery, and others such as irrigation and pesticides) specified in log and rice variety tolerant to flood (1 for the flood tolerant variety and 0 otherwise); b) farm's characteristics, including characteristics of household head (e.g., gender, age and education), assets of household (land and durable consumption assets per capita), soil quality by three categories (low, moderate and high quality), and type of rice planted (early rice, middle rice and late rice); c) year dummies for 2011 and 2012 to control for the effects of other variables that were specifically related to each of the three years (2010, 2011, 2012); and d) province dummies to control for the effects of province-specific factors that do not change over time. θ_1 is a vector of parameters to be estimated. u is an error term that captures the uncertainty, including weather, faced by farmers and satisfies $E(u)$=0.

After estimating equation (1), we calculate the error term $u = y - f_1(A, x, \theta_1)$. The central moments of the yield can be defined as $E(y) = f_1(A, x, \theta_1)$ for the expected value of yield, $E[(u)^2] = f_2(A, x, \theta_2)$ for the variance of yield, and $E[(u)^3] = f_3(A, x, \theta_3)$ for the skewness of yield (Di Falco and Chavas 2009; Kim and Chavas 2003).

Modeling Adaptation to Extreme Weather Events

Two econometric challenges arise in estimating the impact of farmer's adaptation on the three outcome variables. They are the endogeneity of the adoption of farm management practice (*A*) and the sample selection bias due to unobserved heterogeneity. To deal with sample selection bias problem, we employ an endogenous switching regression model to identify the impacts of adjusting farm management practices on the mean, variance and skweness of rice yield. In the switching regression approach, the farmers are partitioned according to the adoption decision as two regimes (e.g., adopters and nonadopters). The farmer will normally choose to take adoptions when there is a net benefit by doing so (Abdulai and Huffman 2014). We can therefore represent farmer *i*'s benefit by a latent variable A_i^* as:

(2) $$A_i^* = g(x, z, D, \gamma) + \eta_i, \quad A_i = 1[A_i^* > 0]$$

where the variable *z* is an instrument variable (IV) for *A* that is going to be an explanatory variable in the outcome equations (mean, variance and skewness of rice yield) discussed below. Here we use whether farmer can access to government's technical service against drought or flood as IV. It is a dummy variable (1=yes; 0 otherwise) measured at village level. *D* includes two dummy variables, the serious drought year (1=yes, 0 otherwise) and serious flood year (1=yes, 0 otherwise) measured at county level. γ denotes a vector of parameters to be estimated. The error term η with mean zero and variance $\sigma_\eta^{\ 2}$ captures measurement errors and factors unobserved.

Given that farmers choose to either adopt the farm management measures or not adopt them, a separate outcome function is specified for adopters and non-adopters as:

（3a）Regime 1 (Adopters): $Q_{1i} = f(A, x, D, \beta_1) + \varepsilon_{1i} \quad if \quad A_i = 1$

（3b）Regime 2 (Nonadopters): $Q_{2i} = f(A, x, D, \beta_2) + \varepsilon_{2i} \quad if \quad A_i = 0$

where Q_{1i} and Q_{2i} are the outcome variables (mean of rice yield in log, variance of rice in log, and skewness of rice yield) for adopters and nonadopters, respectively. The vectors β_1 and β_2 are parameters to be estimated.

The three error terms η, ε_1, ε_2 in equations (2), (3a) and (3b) are assumed to have a trivariate normal distribution, with zero mean and the following covariance matrix:

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

where $Var(\varepsilon_1) = \sigma_1^{\ 2}, Var(\varepsilon_2) = \sigma_2^{\ 2}$, $Var(\eta) = \sigma_\eta^{\ 2}, Cov(\varepsilon_1, \varepsilon_2) = \sigma_{12}$,

$Cov(\varepsilon_1, \eta) = \sigma_{1\eta}$,and $Cov(\varepsilon_2, \eta) = \sigma_{2\eta}$. Note that since Q_{1i} and Q_{2i} are not observed simultaneously, the covariance between ε_1 and ε_2 is actually not defined. The sample selection bias may lead to nonzero covariances between the error terms of the selection equation (2) and the outcome equation (3) (Maddala 1983). According to Lee (1978), the expected values of the error terms ε_1 and ε_2 conditional on the sample selection are given as:

$$(4)\ E[\varepsilon_{1i} \mid A_i = 1] = E(\varepsilon_{1i} \mid \eta > -g(x, z, D, \gamma) = \sigma_{1\eta} \frac{\phi[g(x, z, D, \gamma)/\sigma)]}{\Phi[g(x, z, D, \gamma)/\sigma]} \equiv \sigma_{1\eta}\lambda_{1i}$$

$$(5)\ E[\varepsilon_{2i} \mid A_i = 0] = E(\varepsilon_{2i} \mid \eta \le -g(x, z, D, \gamma) = -\sigma_{2\eta} \frac{\phi[g(x, z, D, \gamma)/\sigma)]}{1 - \Phi[g(x, z, D, \gamma)/\sigma]} \equiv \sigma_{2\eta}\lambda_{2i}$$

where $\phi(\cdot)$ is the standard normal probability density function and $\Phi(\cdot)$ the standard cumulative distribution function. The term of λ_1 and λ_2 refers to the inverse Mills ratio evaluated at $g(x,z,D,\gamma)$, which are incorporated into equation (3) to account for sample selection bias. A more efficient method to estimate the endogenous switching model is full information maximum likelihood (FIML) method (Lokshin and Sajaia 2004). For an adopter and nonadopter of the farm management measures, the expected value of the outcome is calculated respectively as:

(6) $E(y_{1i} \mid A_i = 1) = f(A, x, D, \beta_1) + \sigma_{1\eta}\lambda_{1i}$

(7) $E(y_{2i} \mid A_i = 0) = f(A, x, D, \beta_2) + \sigma_{2\eta}\lambda_{2i}$

Accordingly, the expected value of the same adopter had he chosen not to adopt the farm management measures, and of the same nonadopter had he chosen to adopt is given respectively as:

(8) $E(y_{2i} \mid A_i = 1) = f(A, x, D, \beta_2) + \sigma_{2\eta}\lambda_{1i}$

(9) $E(y_{1i} \mid A_i = 0) = f(A, x, D, \beta_1) + \sigma_{1\eta}\lambda_{2i}$

The change in the outcome due to the adoption of farm management measures can then be specified as the difference between adoption and nonadoption (Di Falco et al. 2011). These changes are termed the average treatment effect on the treated (ATT) as the difference between (6) and (8):

(10) $ATT = E[y_{1i} \mid A_i = 1] - E[y_{2i} \mid A_i = 1]$

$$= f(A, x, D, \beta_1) - f(A, x, D, \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{1i}$$

Similarly, we can also calculate the average effect of the treatment on the untreated (ATU) for the farmers that actually did not adopt as the difference between (9) and (7):

(11) $ATU = E[y_{1i} \mid A_i = 0] - E[y_{2i} \mid A_i = 0]$

$$= f(A, x, D, \beta_1) - f(A, x, D, \beta_2) + (\sigma_{1\eta} - \sigma_{2\eta})\lambda_{2i}$$

Since sample selection is taken into account through the terms (λ_1, λ_2) of equations (10) and (11), *ATT* and *ATU* generates unbiased estimates of the effects of adjusting farm management practices.

Econometric Estimation

Here we present the estimation results of equations (2), (3a) and (3b).

Estimation of Mean Rice Yield Function

We begin by estimating the determinants of adoption of farm management measures and their impact on the mean rice yield. The results for the selection and mean yield equations that are jointly estimated by FIML approach are reported in table 3. The first column reports the estimates of the selection function (1). The second and third columns present, respectively, the estimated coefficients of mean rice yield functions (3a) and (3b) for farmers that did and did not adopt farm management measures. Of significant interest in the results of selection function is the effects of the serious flood and drought on the adoption decision. Previous studies found that there is no strong relationship between climate change variables and farmer's adaption (e.g., Di Falco et al. 2011). Our results show that comparing with the normal year, more farmers tend to adjust their farm management practices when they face the serious drought or flood (rows 1 and 2, table 3). This result empirically confirms that the adoption of farm management measures identified in this study is actually a type of adaptation to extreme weather events such as drought and flood. To simplify discussion, therefore, we also use the term of adaptation to replace the adoption of farm management measures in the rest of this article.

We also find that the impacts of many inputs and farm's characteristics on farmer's adaptation are statistically significant (column 1, table 3). The inputs such as labor, fertilizer, other inputs and flood-tolerant variety have significant positive effects on the probability of adapting the farm management measures. The estimated coefficient for male headed households is negative and statistically significant, suggesting that women tend to be more motivated to adjust farm management practices related to the extreme events. Both land per capita and durable consumption assets per capita have significant and positive effects on adaptation. This result confirms the concerns that the poor may be more vulnerable in face of climatic shocks (Wang et al. 2014).

Instrument variable performances well. It has significant and positive effect on adaptation. This suggests that farmers in the village with access to government's technical service against drought or flood were found to be more likely to take adaptation. To test whether this IV does not directly affect rice yield but has indirect effect on rice yield through its effect on adaptation, the rice yield among farmers that did not adapt is regressed on the variable of the IV along with all other variables. The *t* test statistic is 1.13, suggesting evidence supporting the validity of the IV.

The estimates presented in the last two columns of table 3 account for the endogenous switching in the mean rice yield function. Both the estimated coefficients of the correlation terms ρ_j are not statistically significant (bottom row, table 3). ρ_j (j = 1, 2) reflects the correlation coefficient between the error term of the selection equation (2) and the error term of outcome equations (3a) and (3b), respectively (Lokshin and Sajaia 2004). Hence the results imply that the hypothesis of absence of sample selection bias may not be rejected.

In yield equations, most of estimated coefficients are statistically significant with expected signs. For example, rice yield is lower for both adapters and non-adopters when the extreme weather events are presented. In particular, the impact of flood on the rice yield of nonadopters is larger than that of the adopters. These results suggests that the flood events are serious than drought in rice production. Adopters suffer less yield loss than non-adopters, indicating the effective impact of adaptation. Exception is found for adopters in the serious drought year, the estimated coefficient is not statistically significant. This may be due to the fact that rice is generally planted in the areas where availability of irrigation water is more ensured. Less case of significant coefficients for input variables (rows 3-7, table 3) is consistent with previous findings on intensive or excessive use of production inputs in China (e.g., Huang et al., 2008; Holst et al. 2013).

In terms of the farm's characteristics, most of estimated coefficients are statistically significant. The household headed by male, youth and more educated people tends to improve rice yield for both adopters and nonadopters (in the middle of table 3). The negative impact of land per capita suggests that larger farms generally have lower rice yield, a finding similar to many studies in the literature (Abudulai and Huffman 2014; Chen et al. 2011). Other variables such as wealthy (durable consumption assets per capita) and better soil quality also have positive impact on rice yield. The order of yield from early rice to middle rice and late rice is also expected.

Estimation of risk functions

The estimation results of farmer's adaptation and its impact on variance and skewness of rice yield are included in tables A2 and A3 in Appendix. Because the results on the selection (or adaptation) equation (column 1, tables A2 and A3) are similar with those presented in table 3, here we focus our discussion on the estimates of the variance and skewness functions.

The estimated results show that the covariance term ρ_j in risk functions for both adopters and nonadopters are statistically significant (bottom rows, tables A2 and A3).

Unlike the estimates of mean of rice yield presented in table 3, the estimation for both the variance and skewness function rejects the hypothesis of absence of sample selection bias. This suggests that adaptation would not have the same effect on rice yield risk for the nonadopters if they would take the adaptation due to unobserved heterogeneity (Abdulai and Huffman 2014).

Most of estimated coefficients in the variance function are statistically significant (Tables A2). The signs of many coefficients reveal some interesting findings. For example, the serious flood is found to have statistically positive impact on the variance of rice yield for nonadaoptors, but no significant impact for adopters (row 2, table 2A). This suggests that the adaptation does mitigate rice yield risk or variance when the serious flood occurred. While the impact of the serious drought on the variance is positive but not statistically significant. This may be due to the fact that rice is produced in the regions with good irrigation infrastructure. The impacts of several inputs and farm's characteristics on the variance of yield also differ (in the middle of table 2A).

On the the skewness of rice yield, we first test normality of the error term *u* with the null hypothesis that the yield distribution is symmetric using a Wald statistic. The mean skewness of *u* is -0.35 and the statistic is statistically different from zero with a *p*-value of 0.000. This implies that the distribution of yield is skewed to the left, corresponding to a significant exposure to downside risk. In this case, if the skewness increasingly negative, the probability of crop failure would increase (Torriani et al. 2007).

The results of estimated skewness function suggest both of the serious flood and drought have significantly negative effects on the skewness of rice yield and thus increase the exposure to downside risk for both adopters and nonadopters (rows 1 and

2, table A3). We also find that the inputs such as labor and machinery and better soil quality have difference effects on the skewness of yield for adopter and nonadoptes (in the middle of table A3). The differences in the coefficients of both the variance and skewness function between adopters and nonadopters illustrate the presence of heterogeneity in the sample.

Effects of adaptation on mean, variance and skewness of rice yield

The estimates for the average treatments effects (ATT) and (ATU) on the mean, variance and skewness of rice yield are presented in table 4. The results reveal that the adaptation significantly increases rice yield (rows 1 and 2). Unlike the mean differences presented in table A1, which may confound the impact of farmer's adaptation on yield with the influence of other characteristics, these average treatment effect estimates account for selection bias arising from the fact that adopters and nonadopters may be systematically different. Specifically, in the counterfactual case (8), farmers who actually taken adaptation would have produced about 663 kg/ha (that is about 14%) less if they did not adapt (row 1). In the counterfactual case (9) that farmers that did not adapt, they would have produced about 74 kg/ha (that is about 2%) more if they had adapted (row 2). These findings suggest that adaptation to the extreme weather events through farm management measures does increase rice yield.

Table 4 also present the average treatments effects of adaptation on the variance and skewness of rice yield. We find that farm management measures taken by farmers in response to extreme weather events significantly decreased both variance (rows 3-4) and downside risk of rice yield (rows 5-6). For example, the risk (variance measure) faced by farmers who actually adapted would have an increased 0.021 unit (that is about 43%) if they did not adapt (row 3). The impact of taking adaptation measures on the skweness is similar to its impact on the variance case. The downside risk faced by farmers who actually adapted farm management measures would have an increased of 0.302 unit (that is about 69%) if they did not adapt (row 5). These estimates show that farmer’s adaptation to extreme weather events hedges against the risk of crop failure.

Conclusions

Using data from a survey conducted in five provinces in China, this article investigated the contribution of the adoption of farm management measures in response to the extreme weather events on the mean, variance and downside risk of rice yield. The survey results show that more farmers adjust their farm management practices (e.g., reseeding, fixing and cleaning seedlings) in the serious drought and flood year than in the normal year. The econometric analysis confirms that farmers do respond to the extreme weather events by adopting farm management measures. The extent of adopting farm management measures is closely correlated with crop input levels and varies among households with differences in the characteristics of both farmers and their farms. Moreover, improving farmers’ access to government’s service against drought and flood facilitates farmers to adjust their farm management practices.

The existing farm management measures can help farmer’s adaptation to the extreme weather events. The adaptation through adjusting farm management contributes to the increase in the mean of rice yield and the reduction of risks, including the variance and downside risk of rice yield.

The findings from this study have several policy implications. First, currently, the plans for enhancing the national adaptation strategies have mainly focused on new investment and new technology (IPCC 2014). While these are important, the national adaptation plans should also pay attention to the existing farm practices (e.g., the farm management measures in this study) that can reduce climate risks and can be easily adopted by farmers. However, our survey shows that, even during serious drought and flood years, only one third of farmers are able to use farm management measures to cope with the extreme weather events. As the cost of this kind of adaptation is low, potential to scale up it to more farmers is high. Second, our results also suggest that the government service against drought and flood is of paramount importance in facilitating farmer's adaptation. However, only one fourth of rice farmers in China can access to this service. Clearly, there is great room to incorporate climate change adaptation service into the public extension system in China. The last but not least, as farmers have been suffering the increasing frequency and severity of the extreme weather events in many developing countries, we believe that the findings of this study also have implications to other countries in terms of national adaptation plan and farmer's crop risk management.

References

Abdulai, A., and W. Huffman. 2014. The Adoption and Impact of Soil and Water Conservation Technology: An Endogenous Switching Regression Application. *Land Economics* 90(1): 26-43.

Abedullah, A., and S. Pandey. 2004. Risk and Fertilizer Use in the Rainfed Rice Ecosystem of Tarlac, Philippines. *Journal of Agricultural and Applied Economics* 36(1): 241-250.

Antle, J. M. 1983. Testing the Stochastic Structure of' Production: A Flexible Moment-based Approach. *Journal of Business & Economic Statistics* 1(3): 192-201.

Antle, J. M., and W. J. Goodger. 1984. Measuring Stochastic Technology: the Case of Tulare Milk Production. *American Journal of Agricultural Economics* 66: 342–350.

Chen. H., J. Wang, and J. Huang. 2014. Policy Support, Social Capital and Farmers' Adaptation to Drought in Crop Production of China. *Global Environmental Change* 24,193-202.

Deressa, T. T., R. M. Hassan, C. Ringler, T. Alemu, and M. Yesuf. 2009. Determinants of Farmers' Choice of Adaptation Methods to Climate Change in the Nile Basin of Ethiopia. *Global Environmental Change* 19:248-255.

Di Falco, S., and J. P. Chavas. 2009. On Crop Biodiversity, Risk Exposure and Food Security in the Highlands of Ethiopia. *American Journal of Agricultural Economics* 91: 599–611.

Di Falco, S., and M. Veronesi. 2012. Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation in the Nile basin of Ethiopia, 86th Annual Conference, Warwick University, Coventry, UK 134775, Agricultural Economics Society.

Di Falco, S., M. Veronesi, and M. Yesuf. 2011. Does Adaptation Provide Food Security? A Micro Perspective from Ethiopia. *American Journal of Agricultural Economics* 93(3), 829-846.

FAOSTAT. 2011. Statistics Database. Available at: http://faostat.fao.org.

Foudi, S., and K. Erdlenbruch. 2012. The Role of Irrigation in Farmers' Risk Management Strategies in France. *European Review of Agricultural Economics* 39 (3): 439–457.

Holst, R., X. Yu, and C. Grun. 2013. Climate Change, Risk and Grain Yields in China. *Journal of Integrative Agriculture* 12(7): 1279-1291.

Howden, S. M., J. F. Soussana, and F. N. Tubillo, N. Chhetri, M. Dunlop, and H. Meinke. 2007. Adapting agriculture to Climate Change. *PNAS* 104, 19691-19696.

Huang, J., R. Hu, J. Cao, and S. Rozelle. 2008. Training Programs and In–the–field Guidance to Reduce China's Overuse of Fertilizer without Hurting Profitability. *Journal of Soil and Water Conservation* 63(5): 165-167.

IPCC (Intergovernmental Panel on Climate Change). 2014. *Climate Change 2014: Impacts, Adaptation, and Vulnerability*. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Just, R. E., and R. D. Pope. 1979. Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics* 61: 276-284.

Kim, K., and J. P. Chavas. 2003. Technological change and risk management: an application to the economics of corn production. *Agricultural Economics* 29: 125-142.

Kim, K., J. P. Chavas, B. Barham, and J. Foltz. 2014. Rice, Irrigation and Downside Risk: A Quantile Analysis of Risk Exposure and Mitigation on Korean Farms. *European Review of Agricultural Economics* 3:1-41.

Koundouri, P., C. Nauges, and V. Tzouvelekas. 2006. Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics* 88(3): 657-670.

Lee, L. F., and R. P. Trost. 1978. Estimation of Some Limited Dependent Variable Models with Application to Housing Demand. *Journal of Econometrics* 8:357-382.

Lokshin, M., and Z. Sajaia. 2004. Maximum Likelihood Estimation of Endogenous Switching Regression Models. *Stata Journal* 4(3): 282-89.

Maddala, G. S. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge, U.K.: Cambridge University Press.

NBSC (National Bureau of Statistics in China). 2012. China Statistical Yearbook 2012. China Statistical Press, Beijing.

Seo, S. N., and R. Mendelsohn. 2008. Measuring Impacts and Adaptations to Climate Change: A Structural Ricardian Model of African Livestock Management. *Agricultural Economics* 38: 151–165.

Torriani, D., P. Calanca, M. Lips, H. Ammann, M. Beniston, and J. Fuhrer. 2007. Regional Assessment of Climate Change Impacts on Maize Productivity and Associated Production Risk in Switzerland. *Reg Environ Change* 7: 209-221.

Wang, Y., J. Huang, and J. Wang. 2014. Household and Community Assets and Farmers' Adaptation to Extreme Weather Event: the Case of Drought in China. *Journal of Integrative Agriculture* 13(4): 687-697.

World Bank. 2010. Economics of Adaptation to Climate Change: Synthesis Report. Washington, DC: The World Bank.

Yesuf, M., S. Di Falco, T. Deressa, C. Ringler, and G. Kohlin. 2008. The Impact of Climate Change and Adaptation on Food Production in Low-Income Countries: Evidence from the Nile Basin, Ethiopia. IFPRI Discussion Paper 828, Washington, D.C.

Table 1. Percentage of Plots Affected by the Extreme Weather events (drought or flood) and Yield Loss Reported by Farmers in 2010-2012

	Plots affected by drought or flood (%)		Yield loss when suffered from drought or flood (%)	
	In serious disaster year	In relatively normal year	In serious disaster year	In relatively normal year
Drought [a]	41	16	24	23
Early rice	37	15	26	26
Middle rice	60	22	19	21
Late rice	49	20	26	22
Flood [b]	34	16	25	24
Early rice	44	25	30	27
Middle rice	54	19	17	21
Late rice	22	11	23	20

Source: Authors' survey.

a: A total of 1449 observations in 12 counties.b: A total of 2305 observations in 11 counties.

Table 2. Percentage of Plots with Major Farm Management Measures Adopted by Rice Farmers in 2010-2012

	Reseeding, fixing or cleaning seedlings	Changing varieties in the next season or adjusting fertilize use
Serious disaster year	33	5
Relatively normal year	26	4
Average	30	4.5

Source: Authors' survey.

Note: Sample includes 3754.

Table 3. Estimations of Farmer's Adaptation and Its Impact on Mean Rice Yield

		Rice yield (log)	
	Selection	Adopters	Nonadopters
Serious disaster years			
Drought	0.117**	0.009	-0.124***
	(2.218)	(0.338)	(5.424)
Flood	0.277***	-0.095***	-0.273***
	(6.296)	(4.611)	(11.745)
Inputs			
Labor (log)	0.100***	-0.000	0.016
	(5.189)	(0.040)	(1.634)
Fertilizer (log)	0.087***	0.079***	0.021
	(3.166)	(4.154)	(1.331)
Machinery (log)	0.001	0.000	0.014***
	(0.154)	(0.036)	(3.839)
Other inputs (log)	0.031***	0.010	0.015**
	(2.640)	(1.486)	(2.513)
Flood-tolerant variety	0.122***	0.049**	0.015
	(3.447)	(2.469)	(0.916)
Farm's characteristics			
Male of household head	-0.245**	0.147*	0.128*
	(2.058)	(1.648)	(1.674)
Age of household head	-0.003	-0.003***	-0.003***
	(1.642)	(2.960)	(3.469)
Education of household	0.007	0.001	0.008***
	(1.326)	(0.291)	(2.908)
Land per capita	0.138***	-0.002	-0.028**
	(5.843)	(0.137)	(2.130)
Durable consumption assets per capita	0.001***	0.001***	0.001***
	(3.648)	(3.519)	(5.950)
Moderate soil quality	0.010	0.033	0.098***
	(0.203)	(1.602)	(3.989)
High soil quality	-0.034	0.086***	0.146***
	(0.603)	(3.187)	(5.287)
Middle rice	-0.046	0.218***	0.257***
	(0.991)	(8.307)	(10.848)
Late rice	-0.050	0.079***	0.144***
	(1.384)	(3.661)	(7.696)
D2011	0.174***	0.220***	0.131***
	(3.324)	(5.385)	(4.620)
D2012	0.112**	0.143***	0.113***
	(2.272)	(4.491)	(5.088)
Instrument variable			
Access to government's technical service against drought or flood	0.108***		
	(2.789)		
Constant	-0.479	8.055***	8.243***
	(1.483)	(36.077)	(49.539)
Province dummies	Yes	Yes	Yes
σ_i		0.382**	0.542**
		[0.047]	[0.023]
ρ_j		0.085	-0.045
		[0.225]	[0.040]

Note: Absolute *z*-values in parentheses and *p*-value in square brackets. *, ** and *** represent the statistically significant at 10%, 5% and 1%, respectively. The sample is 7508 (3754×2 years).

Table 4. Impacts of Farm Management Measures on Mean, Risk and Downside Risk Exposure of Rice Yield

Sub-samples	Decision stage		Treatment effects
	To adopt	Not to adopt	
Average expected rice yield (kg/ha)			
Rice plots that adopted	5571	4908	TT= 663***
Rice plots that did not adopt	5161	5086	TU= 74***
Average expected variance (risk)			
Rice plots that adopted	0.028	0.049	TT= -0.021***
Rice plots that did not adopt	0.016	0.035	TU= -0.019***
Average expected skewness (downside risk exposure)			
Rice plots that adopted	-0.136	-0.438	TT= 0.302***
Rice plots that did not adopt	-0.173	-0.487	TU= 0.314***

Note: TT represents the effect of the treatment (i.e., adoption) on the treated (i.e., farmers that adopted). TU represents the effect of the treatment (i.e., adoption) on the untreated (i.e., farmers that did not adopt).

Appendix

Table 1A. Descriptive Statistics of Variables by Adopters and Nonadopters of Farm Management Measures

Variables	Total	Adopters	Non-adopters	Diff.
Rice yield (kg/ha)	5631.13	5854.71	5537.50	317.21***
Variance of rice yield	0.25	0.15	0.30	-0.15***
Skewness of rice yield	-0.35	-0.14	-0.44	0.30***
Serious flood year (1=yes; 0=no)	0.31	0.36	0.29	0.07***
Serious drought year (1=yes; 0=no)	0.19	0.21	0.19	0.02**
Labor (days/ha)	125.41	138.72	119.83	18.89***
Fertilizer (kg/ha)	405.56	413.97	402.03	11.94***
Machinery (yuan/ha)	1807.27	1778.93	1819.14	-40.21*
Other inputs (yuan/ha)	1173.78	1235.09	1148.11	86.98***
Flood-tolerant variety (1=yes; 0=no)	0.28	0.32	0.26	0.06***
Male of household head (1= male; 0= female)	0.98	0.98	0.98	0.00
Age of household head (years)	54.13	53.88	54.23	-0.35
Education of household head (years)	6.63	6.78	6.57	0.21***
Land per capita (ha)	0.34	0.40	0.32	0.08***
Durable consumption assets per capita (1,000 yuan)	23.98	26.94	22.73	4.21***
High soil quality (1=yes; 0=no)	0.22	0.21	0.23	-0.02
Moderate soil quality (1=yes; 0=no)	0.66	0.67	0.65	0.02
Middle rice (1=yes; 0=no)	0.25	0.26	0.25	0.01
Late rice (1=yes; 0=no)	0.39	0.38	0.39	-0.01
2012 (1=yes; 0=no)	0.47	0.44	0.49	-0.05***
2011 (1=yes; 0=no)	0.30	0.35	0.28	0.07***
Access to government's technical service against drought or flood (1=yes; 0=no)	0.24	0.26	0.23	0.03**

Note: the total observations are 7508.

Table 2A. Estimations of Farmer's Adaptation and Its Impact on Variance of Rice Yield

		Variance of rice yield (log)	
	Selection	Adopters	Nonadopters
Serious disaster years			
Drought	0.065	0.254	0.167
	(1.287)	(1.202)	(1.335)
Flood	0.214***	-0.225	0.662***
	(5.197)	(1.351)	(6.385)
Inputs			
Labor (log)	0.076***	-0.236***	0.130***
	(4.430)	(3.320)	(2.993)
Fertilizer (log)	0.045*	-0.000	-0.032
	(1.777)	(0.004)	(0.551)
Machinery (log)	-0.001	-0.021	-0.064***
	(0.194)	(0.901)	(4.573)
Other inputs (log)	0.030***	-0.156***	0.025
	(2.726)	(3.225)	(0.973)
Flood-tolerant variety	0.081**	-0.282**	0.046
	(2.500)	(2.130)	(0.557)
Farm's characteristics			
Male of household head	-0.211*	0.537	-0.886***
	(1.949)	(1.236)	(3.122)
Age of household head	-0.002	0.011*	0.001
	(1.518)	(1.693)	(0.313)
Education of household	0.008	-0.045**	-0.016
	(1.599)	(2.166)	(1.240)
Land per capita	0.116***	-0.346***	0.336***
	(5.379)	(4.079)	(5.783)
Durable consumption assets per capita	0.001***	-0.005***	0.002***
	(4.019)	(3.550)	(2.627)
Moderate soil quality	0.019	0.023	-0.281**
	(0.434)	(0.128)	(2.524)
High soil quality	-0.055	0.399*	-0.538***
	(1.068)	(1.891)	(4.227)
Middle rice	-0.075*	-0.208	-1.034***
	(1.745)	(1.188)	(9.706)
Late rice	-0.054	-0.199	-0.556***
	(1.605)	(1.446)	(6.654)
D2011	0.089*	-0.890***	-0.946***
	(1.839)	(4.443)	(7.824)
D2012	0.068	-0.965***	-1.129***
	(1.498)	(5.286)	(10.195)
Instrument variable			
Access to government's technical service against drought or flood	0.085***		
	(4.229)		
Constant	-0.317	-0.512	0.412
	(1.093)	(0.442)	(0.494)
Province dummies	Yes	Yes	Yes
σ_i		3.810*	2.855**
		[0.085]	[0.035]
ρ_j		-0.965***	0.908***
		[0.004]	[0.006]

Note: Absolute *z*-values in parentheses and *p*-value in square brackets. *, ** and *** represent the statistically significant at 10%, 5% and 1%, respectively. The sample is 7508.

Table 3A. Estimations of Farmer's Adaptation and Its Impact on Skewness of Rice Yield

		Skewness of rice yield	
	Selection	Adopters	Nonadopters
Serious disaster years			
Drought	0.115**	-0.130***	-0.201**
	(2.175)	(2.724)	(2.284)
Flood	0.278***	-0.347***	-0.781***
	(6.327)	(4.435)	(8.462)
Inputs			
Labor (log)	0.101***	-0.059*	0.089**
	(5.233)	(1.824)	(2.159)
Fertilizer (log)	0.085***	0.079*	-0.012
	(3.112)	(1.943)	(0.207)
Machinery (log)	0.001	-0.017***	0.045***
	(0.188)	(2.967)	(3.320)
Other inputs (log)	0.033***	-0.015	0.028
	(2.810)	(1.106)	(1.074)
Flood-tolerant variety	0.124***	0.066	0.043
	(3.501)	(1.155)	(0.642)
Farm's characteristics			
Male of household head	-0.245**	0.326	0.044
	(2.066)	(0.858)	(0.169)
Age of household head	-0.003*	-0.003	-0.008***
	(1.664)	(0.757)	(2.603)
Education of household	0.007	0.000	0.006
	(1.328)	(0.045)	(0.503)
Land per capita	0.138***	-0.056	-0.076
	(5.844)	(1.096)	(1.365)
Durable consumption assets per capita	0.001***	0.001*	0.002***
	(3.656)	(1.790)	(3.106)
Moderate soil quality	0.010	-0.087**	0.150
	(0.201)	(2.504)	(1.451)
High soil quality	-0.034	-0.120*	0.070
	(0.602)	(1.796)	(0.578)
Middle rice	-0.042	0.408***	0.589***
	(0.897)	(3.795)	(5.227)
Late rice	-0.070*	0.262***	0.466***
	(1.927)	(3.282)	(6.048)
D2011	0.175***	0.482***	0.505***
	(3.387)	(4.460)	(4.079)
D2012	0.112**	0.324***	0.422***
	(2.285)	(3.762)	(4.591)
Instrument variable			
Access to government's technical service against drought or flood	0.105***		
	(2.854)		
Constant	-0.421	-0.781	-1.457**
	(1.297)	(1.134)	(2.441)
Province dummies	Yes	Yes	Yes
σ_i		1.226*	2.299**
		[0.099]	[0.040]
ρ_j		0.024**	-0.013**
		[0.027]	[0.033]

Note: Absolute *z*-values in parentheses and *p*-value in square brackets. *, ** and *** represent the statistically significant at 10%, 5% and 1%, respectively. The sample is 7508.