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Mitigating rice production risks from drought through improving irrigation infrastructure and management in China*

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Rice, China's most important food crop, is highly dependent on irrigation, but an increasing number of extreme drought events have challenged rice production in many regions. This paper investigates the role of local irrigation infrastructure in improving farmers' ability to respond to drought and its effectiveness in mitigating the drought risk in rice production in China. The analysis relies on a moment-based specification of the stochastic production function, capturing mean, variance and skewness effects. Using household survey data from 86 villages in five provinces, we jointly estimate farmers' adaptive irrigation decisions and their effects on rice yield and production risk. Our econometric analyses show that irrigation infrastructure in villages contributes to enhancing farmers' irrigation capacity in adapting to drought, and increased irrigation leads to a significant increase in mean yield and a reduction in exposure to risk as well as downside risk in rice production. The paper concludes with policy implications.

Key words: adaptation, China, drought risk, irrigation, rice.

1. Introduction

Rice is the most important food crop in China. In 2014, according to the National Bureau of Statistics of China (NBSC 2015), it accounted for 27 per cent of grain area and 34 per cent of grain production. Despite a reduction in the area devoted to rice production, China's rice production increased from 140 million tonnes in 1980 to 207 million tonnes in 2014 as the result of an increase in yield per hectare from 4.13 to 6.9 tonnes over the same period.

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However, the annual growth rate of rice yield decreased from 2.8 per cent in the 1980s to <1 per cent in the past decade (NBSC 2015).

An increasing number of extreme drought events further challenge China's rice production (Peng *et al.* 2009; Zhang 2014). The Intergovernmental Panel on Climate Change (IPCC 2014) has warned that in the context of climate change, drought events will become more intense and more frequent in tropical and subtropical regions. Extreme drought could affect rice production through its impact on water supply and demand (Wang *et al.* 2013). Since rice production is highly dependent on irrigation, adapting to a rise in the number of extreme drought events, especially through improving irrigation infrastructure and irrigation management, is critically important. Investment in irrigation infrastructure has been proposed as an option to increase agricultural production and ensure national food security (Lohmar *et al.* 2003; Huang *et al.* 2006).

In order to achieve better understanding of the role of irrigation infrastructure in mitigating rice production risks resulting from extreme drought events, several questions need to be answered. How do rice farmers respond to drought through irrigation? What is the role of local irrigation infrastructure in improving farmers' ability to adapt to drought events through changing irrigation? How effective is farmers' adaptation through irrigation in mitigating the drought risk in rice production? Although there are an increasing number of studies on farmers' adaptation to climate change (Deressa *et al.* 2009; Di Falco *et al.* 2011; Wang *et al.* 2014; Huang *et al.* 2015), few empirical studies are available on the role of irrigation infrastructure in farmers' responses to climate risk and the effectiveness of farmers' adaptive irrigation management in mitigating that risk. Most previous studies have focused either on the role of household social capital and other characteristics, or on government policies to support farmers' responses to extreme drought, flood and other events (e.g. Di Falco and Bulte 2013; Chen *et al.* 2014; Wang *et al.* 2015), or on the effects of irrigation water on agricultural output (e.g. Abedullah and Pandey 2004; Huang *et al.* 2006; Holst *et al.* 2013).

The overall goals of this study are to provide empirical evidence of the role of local irrigation infrastructure in improving farmers' ability to respond to drought through changing irrigation, and the effectiveness of irrigation adjustment in mitigating the drought risk in rice production. Although the investment in irrigation infrastructure by local governments or communities is not specifically for responding to climate change, it could be useful for reducing the impacts of occurred changes in climate or extreme drought. To achieve the above goals, we have three specific objectives. First, we investigate to what extent farmers respond to drought through the use of irrigation. Second, we examine the role of local irrigation infrastructure in farmers' responses to drought by changing irrigation. Third, we analyse the effectiveness of farmers' adaptive irrigation in reducing rice yield loss and exposure to risk.

The rest of this paper is organised as follows. The next section introduces the sampling survey and data used in this study. The third section provides descriptive analyses on drought, farmers' irrigation, local irrigation infrastructure and rice yield. After explaining the analytical framework in the fourth section, the fifth section presents the estimated results. The last section concludes with policy implications.

2. Data

The data used in this study are from a field survey that was conducted from late 2012 to early 2013 in five rice planting provinces in South China. Although these provinces may not fully represent China's rice production, they cover a double-season indica rice (early-season rice and late-season rice) production region (Guandong), a double-season and a single-season indica rice (the middle-season rice) production region (Jiangxi), a single-season indica rice (middle-season rice) production region (Yunnan), a single-season indica and japonica mixed rice (middle-season rice) production region (Henan) and a single-season japonica rice production region (Jiangsu).

We applied the stratified random sampling approach to select samples. Within each province, we first selected all counties that had experienced a most severe drought or flood in any of the past 3 years (2010–2012). China's national standard for natural disasters, set by the China Meteorological Administration (CMA 2007), rates the severity of a drought or flood in four categories: 1 = most severe, 2 = severe, 3 = moderate and 4 = little. Second, from the counties identified in the first step, we kept only counties that also experienced a 'normal year' in any of the past 3 years.

During our sampling, we always selected the most recent normal or drought year to reduce the difficulty of farmers' recall. Based on our data, 50.0 per cent of these years are in 2012, 49.6 per cent in 2011 and 0.4 per cent in 2010. Since our survey was organised towards the end of 2012, it means that 50.0 per cent are in the current year; 49.6 per cent are based on farmers' recall of the previous year; and only 0.4 per cent based on farmers' recall from 2 years before that. In addition, we found that farmers had no difficulty recalling crop yield, irrigation and major inputs in severe disaster years in 2011 or 2010 because they had a deep impression of what had occurred during the most recent drought year. In our sample, 85 per cent of the sample in 2011 and 2010 belongs to a severe drought year.

Crop production often faces various weather shocks during any growing season; therefore, the term 'normal year' is relative and defined as a year with no more than moderate (natural disaster level 3) weather shocks. Finally, from the list of counties identified in the second step, three counties in each province except for Jiangxi (10 counties, as we had more funding in Jiangxi) and Guangdong (six counties, as we also had more funding in Guangdong) were randomly selected for survey.

Townships and villages were further selected before we interviewed households. Within each county, all townships were divided into three groups with equal numbers of townships, based on agricultural production infrastructure (above average, average and below average—subjective opinions by the officials from Agricultural Bureau in each county), and one township was randomly selected from each group. The same approach was used to select three villages from each township. Finally, we randomly selected ten households for face-to-face interviews in each sampled village. In each household, two plots with grain production were randomly selected.

From the above samples, we use all household samples with rice production in the 12 rice-producing counties that suffered the severe drought, as this study focuses on farmers' responses to drought. This limits the sample to 1,080 households ($10 \times 3 \times 3 \times 12$) and 2,160 plots. However, because some households either did not plant rice or planted rice in only one of 2 years (drought and normal years) or planted rice in only one plot, the final sample used includes 693 households and 1,013 plots over 2 years from 86 villages in 30 townships of 12 counties. Because farmers in our samples also planted double-season rice (early-season and late-season rice), we analysed data by type of rice: early-season rice; middle-season (single-season) rice; and late-season rice. Thus, we finally obtained 1,449 observations. For each observation in each plot, we collected data for two time periods during the years 2010–2012: severe drought year and normal year; the time (or year) differs across counties.

Although the survey covers a wide range of information, given the goals of this study, our analysis uses only the following data: (i) characteristics of households and rice plots; (ii) detailed information on rice production inputs (e.g. plot area, labour input, fertiliser and pesticide use, machinery use, rice varieties) and outputs in both the drought year and normal year; (iii) irrigation practices at plot level (e.g. irrigation times per season); and (iv) irrigation infrastructure condition at the village level.

3. Drought, farmers' adaptive irrigation and rice yield

3.1 Impact of drought on rice yield

Overall, drought is an increasing problem and becoming more severe in the sampled provinces. For example, from 1980 to 2011, the annual average crop area in the sampled provinces suffering from drought expanded from 2.8 million hectares to 3.4 million hectares, an increase of 22 per cent (NBSC 2012). Over the same period, the proportion of crop area hit by drought increased from 36 per cent to 66 per cent (NBSC 2012). Moreover, the share of seriously damaged area (a yield loss of at least 30 per cent) in a drought-hit area (a yield loss of at least 10 per cent) increased from 11 per cent in 1980 to 23 per cent in 2011 (Ministry of Water Resources of the People's Republic of China 2012; NBSC 2012).

Table 1 Rice yield (kg/ha) in the normal year and drought year, 2010–2012

	Number of samples	Average	Normal year (1)	Drought year (2)	Difference (%) (3) = ((2) − (1))/(1) × 100
Average	1,449	6,692	6,927	6,456	−6.8***
Early-season rice	530	6,280	6,474	6,045	−6.6**
Middle-season rice	394	7,309	7,439	7,178	−3.5*
Late-season rice	525	6,645	7,000	6,289	−10.2***

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Source: Authors' survey.

Our descriptive statistics also demonstrate the severity of drought in the study areas. As shown in Table 1, rice yield is negatively related to drought. For example, the average yield in the drought year (6,927 kg/ha) was 6.8 per cent lower than that in the normal year (6,456 kg/ha) (row 1, column 4). The yield difference between the drought and normal years was also statistically significant for each of three seasons of rice (rows 2–4). Because these results were reported by farmers, the figures in Table 1 accounted for farmers' responses to drought.

3.2 Farmers' adaptive irrigation to reduce drought risk

Changes in the use of irrigation are considered to be an important adaptation to climate change (Negri *et al.* 2005; Kirby and Mainuddin 2009; Finger *et al.* 2011).[1] In our paper, we used changes in the frequency of irrigation times over the total growing season as the measure of adjustment. It is also an important measure of water supply reliability and has been widely applied in agricultural economics to assess irrigation water management performance (e.g. Guo 2004; Liu *et al.* 2008).

The field survey reveals that when faced with drought, some farmers adapt by increasing irrigation applications to reduce risk. Overall, around 39 per cent of farmers in our sample increased the number of irrigation applications in the drought year, compared to the normal year. In rice production, farmers irrigated 6.65 times in the normal year and 7.43 times in the drought year, an increase of 12 per cent (row 1, Table 2). The difference in irrigation applications between the normal year and the drought year is statistically significant at 1 per cent.

[1] Farmers can select from an arsenal of alternatives to respond to the climate abnormality. For example, crop-switching could be one of the fundamental responses to drought. A series of previous studies have examined how farmers respond to climate change by changing crops (Kurukulasuriya and Mendelsohn 2008; Seo and Mendelsohn 2008; Wang *et al.* 2010; Moniruzzaman 2015). All of the above-mentioned adaptation studies find that farmers adjust crops to both temperature and precipitation levels. For example, the studies in China find that farmers in warmer temperatures are more likely to choose cotton, rice and maize, but less likely to choose vegetables, soybeans and potatoes. As precipitation increases, farmers are more likely to choose wheat and less likely to choose vegetables, potatoes and rice (Wang *et al.* 2010). Due to data limitations, this paper does not discuss farmers' crop choice.

Table 2 Relationship between irrigation infrastructure in villages and farmers' irrigation times, 2010–2012

	Irrigation times		
	Average	Normal year	Drought year
All samples	7.04	6.65	7.43
Small reservoirs in villages			
No	6.85	6.44	7.27
Yes	7.70	7.41	7.98
Pond density in villages			
Low	6.32	6.03	6.59
Medium	7.16	6.82	7.49
High	7.59	7.04	8.17
Irrigation station density in villages			
Low	6.38	6.05	6.71
Medium	7.11	6.51	7.72
High	7.87	7.51	8.23

Note: Sample includes 1,449 observations in both normal and drought years. *Source:* Authors' survey.

Why did some farmers increase irrigation applications in the face of drought, while others did not? One possible reason might be access to different types of irrigation infrastructure. As shown in Table 2, farmers from villages that had small reservoirs were more likely to increase irrigation times than those without small reservoirs. The pond density at the village, measured by the number of ponds per hectare of cultivated land, is also positively related to irrigation times. That is, farmers in villages with a high density of ponds and therefore better irrigation infrastructure were more likely to increase the use of irrigation in response to drought. This is because ponds can generally store rainfall water and provide farmers with access to irrigation water when drought occurs. Moreover, a positive relationship is also found between irrigation times and irrigation station density, which is measured as the number of irrigation stations per 100 ha of the village's cultivated land (rows 7–9). The above analysis implies that if local communities have better irrigation infrastructure, farmers' access to irrigation water is likely to increase and their adaptive capacity against drought is also likely to be enhanced.

Does adaptive irrigation play a positive role in helping farmers to increase yield? As shown in Table 3, irrigation applications are positively related to

Table 3 Relationship between irrigation times and rice yield, 2010–2012

Irrigation frequency	Irrigation times	Rice yield (kg/ha)		
		Average	Normal year	Drought year
Low	1.51	5,476	5,696	5,245
Medium	5.36	6,777	7,072	6,480
High	12.97	7,369	7,590	7,232

Note: Sample includes 1,449 observations in both normal and drought years. *Source:* Authors' survey.

rice yield. For example, at low irrigation frequency (average irrigation applications = 1.51), the average rice yield was only about 5,476 kg/ha. However, it increased to 7,369 kg/ha with high irrigation frequency (average irrigation applications = 12.97). Even in the drought year, it is also found that rice yield was higher with increased irrigation times. This information suggests that farmers' adaptive responses through irrigation help to deal with drought risk in rice production.

4. Model and estimation method

We use a production function approach to estimate the effectiveness of farmers' adaptive irrigation in dealing with drought. The simplest approach to estimating a production function with irrigation as an input is to apply the method of ordinary least squares (OLS). This approach, however, might yield biased and inconsistent parameter estimates because it assumes that adaptive irrigation to drought is exogenously determined, whereas it is indeed endogenous. Therefore, the econometric framework employed in this paper to account for the endogeneity of the adaptation decision follows a two-stage instrumental variable approach.

In the first-stage regression, the variable of irrigation times (A) is regressed on a set of instruments and control variables with the following specification:

$$A_{ikvct} = \beta_0 + \beta_1 D_{ct} + \beta_2 D_{ct} \times S_{vct} + \beta_3 H_{ikvct} + \beta_4 C_{ikvct} + \beta_5 P + u_{ikvct}, \quad (1)$$

where subscripts k and i represent the kth plot in the ith household; v and c represent village and county, respectively; and t represents the year (2010–2012). D_{ct} is the drought dummy variable measured at county level. It equals 1 if the county experienced a severe drought shock in year t and equals 0 if the county experienced a normal year. For details, see the discussion in Section 2.

S_{vct} is a vector with three variables measured at the village level and is used to reflect the irrigation infrastructure we discussed earlier: village with small reservoirs (yes = 1, no = 0); pond density (number of ponds per hectare of cultivated land); and irrigation station density (number of irrigation stations per 100 ha of cultivated land). The interactions, $D_{ct} \times S_{vct}$, are included to measure the change in the difference in irrigation times between the severe drought year and normal year. If the village-level infrastructure could help farmers to enhance irrigation and reduce exposure to drought shock, we would expect the coefficients of $D_{ct} \times S_{vct}$ (i.e. β_2) to be positive.

We identify irrigation infrastructure as the suitable instrument for farmers' adaptive irrigation. Logically, the irrigation infrastructure meets the criteria for an appropriate instrument: it affects the endogenous variable, irrigation, but not rice yield, except through its impact on irrigation. One concern about the instrument is that there might be other connections between village's irrigation infrastructure and rice yields. However, as we will illustrate below, the validity of the instruments has also been scrutinised by statistical tests.

To control for the impacts of other factors, Equation (1) also includes several control variables. The first set of variables, H_{ikvct}, is a vector of variables reflecting household and farm characteristics. It includes (i) characteristics of household head (e.g. age and education); (ii) primarily male labour engaged mainly in farming (yes = 1, no = 0); (iii) primarily female labour engaged mainly in farming (yes = 1, no = 0); (iv) per capita land (ha); (v) family wealth, measured by the value of the household's durable consumption assets (in 10,000 RMB yuan); (vi) soil types measured at the plot level, which is either loam (yes = 1, no = 0) or clay soil (yes = 1, no = 0), and compared against sandy soil; and (vii) other farmland characteristics, measured as saline land (yes = 1, no = 0) and plain land (yes = 1, no = 0).

Equation (1) also includes crop, year and provincial dummies. The crop dummies, C_{ikvct}, are included to control for the likely differences among three types of rice crops (early-, middle- and late-season rice). P indicates a set of year and province dummies. The year dummies control for the plot-invariant annual characteristics in the dependent variable that are common across plots, such as changes in environmental and natural resource policies. The province dummies capture the effects of time-invariant province-specific factors, such as climate, environment and agricultural policy. $\beta_j (j = 0, \ldots, 5)$ is a parameter vector to be estimated. u_{ikvct} is an error term. Summary statistics of the dependent and independent variables are presented in Table A1 of Appendix S1.

Finally, since Equation (1) is specified for a count data outcome (non-negative integer-value), the OLS estimates could be biased. We thus use the negative binomial regression method to estimate Equation (1).

In the second stage of analysis on the effects of adaptive irrigation on rice yield and production risk, a stochastic rice yield function y in log form can be defined as

$$\begin{aligned} y_{ikvct} &= f(x, a) + e \\ &= \alpha_0 + \alpha_1 A_{ikvct} + \alpha_2 A_{ikvct}^2 + \alpha_3 D_{ct} + \alpha_4 X_{ikvct} \\ &\quad + \alpha_5 H_{ikvct} + \alpha_6 C_{ikvct} + \alpha_7 P + e_{ikvct}, \end{aligned} \tag{2}$$

where e is a random variable with mean zero that reflects production risk (e.g. unpredictable weather effects) and A_{ikvct} denotes irrigation times as defined in Equation (1). Note that in Equation (2), we also include a quadratic form of irrigation times (A_{ikvct}) to identify the possible nonlinear relationship between adaptive irrigation and rice production. X is a set of production input variables (e.g. labour, fertiliser, machinery and other inputs) specified in log form and drought-tolerant rice variety (1 for drought-tolerant variety, 0 otherwise).[2] Other variables (e.g. H_{ikvct}, C_{ikvct} and P) are the same as those defined in Equation (1), and a is a vector of parameters to be estimated.

[2] The other input variable is constructed by adding the total costs of chemical insecticides, fungicides and herbicides.

To measure the production risk, we follow the method suggested by Antle (1983) and assess the rice production risk by relying on a moment-based approach, which allows production risk exposure to be represented by the moments of the production function $f_1\ (x,a_1)$. This approach has been widely applied in agricultural economics to model the implications of production risk management (e.g. Kim and Chavas 2003; Koundouri *et al.* 2006; Di Falco and Chavas 2009; Di Falco and Veronesi 2014; Huang *et al.* 2015) and can generate consistent estimates of the residuals: $e_1 = y\text{-}f_1\ (x,a_1)$. Since e_1 captures the uncertainty in rice production after controlling for the effects of other factors, this provides a basis from which to estimate all relevant moments of rice yield, conditional on x (Kim *et al.* 2014). Based on the sample information, it follows that $f_1\ (x,a_1) \equiv E(y)$ is the mean of rice yield, which is the first central moment.

We then capture the extent of risk exposure by the second (variance) and third (skewness) moment of the distribution of yield as follows:

$$e_1^2 = f_2(x, a_2) + \varepsilon_2, \tag{3}$$

$$e_1^3 = f_3(x, a_3) + \varepsilon_3. \tag{4}$$

Note that an increase in skewness implies a reduction in downside risk exposure, which implies a reduction in the probability of crop failure (Di Falco and Veronesi 2014).

Because the error term e in Equation (2) is being used to estimate the distribution of risk exposure, the consistent estimate of e is crucial in the estimation of higher moment functions in Equations (3) and (4). Along with previous studies (e.g. Huang *et al.* 2015), we specify the first and second moment functions as exponential functions to ensure non-negative mean and yield variance, and the third moment function as linear to reduce multicollinearity problems.

A final econometric issue concerns the standard errors of the estimates. In our sampling, we collected ten households in each selected village to survey, neglecting the different size across villages and townships. This means that we do not undertake the probability proportional to size (PPS) sampling. In addressing this, all regressions are weighted by the ratio of village population (in terms of number of households) to county population. In addition, to address potential heteroscedasticities, we report the robust standard errors and cluster the standard errors at the village level.

5. Estimation results

The econometric method presented in Section 4 was applied using plot-level data on rice production in China. The empirical result discussions start with an analysis of the determinants of irrigation times and then follow its effects on rice yield and risks.

5.1 Determinants of irrigation times

The results presented in Table 4 demonstrate that the first stage of our model in Equation (1) generally performed well in explaining irrigation (column 1). In general, the signs of the estimated coefficients on the control variables are as expected and reasonable. Household and farm characteristics are found to have significant impacts on the irrigation decision. For example, households headed by highly educated people tend to have fewer irrigation times. The positive coefficient of land per capita suggests that the larger the farm size, the more attention is paid to irrigation, a finding similar to previous studies

Table 4 Estimated results on irrigation times and rice yield

Variables	(1) Irrigation times	(2) Rice yield (log)
Irrigation times		0.14*** (0.04)
Irrigation times square		−0.01*** (0.00)
Drought	−0.15** (0.06)	−0.11*** (0.03)
Drought interaction with irrig. infrastructure		
With small reservoir × drought	0.32*** (0.11)	
Number of ponds/ha of cultivated land in village × drought	0.07** (0.04)	
Number of irrigation stations/100 ha of cultivated land × drought	0.07*** (0.03)	
Inputs		
Labour (log)		0.07*** (0.02)
Machinery (log)		0.02* (0.01)
Fertiliser (log)		−0.01 (0.03)
Other inputs (log)		0.01 (0.02)
Drought-tolerant variety		−0.03 (0.04)
Household and farm characteristics		
Primarily male labour, engaged mainly in farming (yes = 1, no = 0)	0.06 (0.08)	−0.02 (0.04)
Primarily female labour, engaged mainly in farming (yes = 1, no = 0)	−0.13 (0.10)	0.03 (0.05)
Age of household head	0.00 (0.00)	−0.00 (0.00)
Education of household head	−0.02** (0.01)	0.01 (0.01)
Land/capita (ha)	0.07*** (0.03)	0.03 (0.02)
Durable consumption assets (100k yuan)	0.03 (0.03)	0.02* (0.01)
Plain land (yes = 1, no = 0)	0.33*** (0.09)	0.12 (0.07)
Loam soil (yes = 1, no = 0)	−0.17* (0.09)	0.00 (0.05)
Clay soil (yes = 1, no = 0)	−0.09 (0.10)	0.07 (0.05)
Saline soil (yes = 1, no = 0)	0.23** (0.10)	−0.09 (0.06)
Crop dummies (base is early-season rice)		
Middle-season rice (yes = 1, no = 0)	0.01 (0.11)	0.15** (0.06)
Late-season rice (yes = 1, no = 0)	0.14** (0.06)	−0.04 (0.04)
Constant	3.23*** (0.46)	7.51*** (0.47)
Year dummies	Yes	Yes
Province dummies	Yes	Yes

Note: Both regressions are weighted by the ratio of village population (in terms of number of households) to county population. The robust standard errors, clustered at the village level, are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample is 2,898 (1,449 × 2 years).

(e.g. Huang *et al*. 2015). Farmers are more likely to increase irrigation on the plots in plains areas. The reason might be that the cost of irrigation is generally higher in hillside areas. Poor soil quality (sandy or saline soil) is found to increase water requirements and thus may increase the production risk related to drought. This, in turn, induces farmers to enhance irrigation.

More importantly, the regression analysis illustrates the significance of local irrigation infrastructure to farmers' irrigation responses to drought. As shown in Table 4, drought has a significantly negative effect on farmers' irrigation times when the local infrastructure condition is poor. For instance, when shocked by drought, farmers in villages with no irrigation infrastructure experienced a 0.150 decrease in irrigation times. However, the positive and highly significant coefficients on all the three interaction terms mean that farmers in villages with good infrastructure increase irrigation times sharply compared to those with poor infrastructure. This indicates that irrigation infrastructure is relevant to farmers' irrigation responses to drought.

We also checked the validity of the IV by conducting the following tests. First, we conducted a weak instrument test. The results show that the IV is statistically significant at the 1 per cent level in the first-stage model. We rejected the null hypothesis of weak instruments. (Wald test statistics are 20.62 for the linear and 20.94 for the quadratic form of irrigation times, both exceeding the critical value even if we are willing to tolerate a relative bias of 5 per cent).

Second, as in Di Falco *et al*. (2011), we conducted a test to see whether the IV does not directly affect rice yield but has an indirect effect on yield through its effect on irrigation times. To do this, the rice yield among farmers who did not irrigate is regressed on the IV along with other control variables. The Chi-square test statistic is 3.33 (P-value = 0.19), suggesting evidence of no direct impact of the IV on rice yield.

Third, we made a balance test on the pretreatment characteristics of villages that have different scales of irrigation infrastructure. Results indicate that these villages are similar in most other pathways. Moreover, we estimated the model conditioned on village fixed effects. As in the case of province fixed effects estimation, we came to a similar conclusion.

5.2 Impacts of adaptive irrigation on mean yield

The results of the mean function establish a significantly nonlinear effect of adaptive irrigation on mean yield (Table 4). The turning point value is at an average 13 irrigation times, which means that during the whole rice-growing season below the average of 13 irrigation times any increase in irrigation increases mean yield, but above 13 an increase in irrigation is related to a decrease in mean yield. This is consistent with diminishing marginal expected productivity. These results are a little higher than previous rice field experimental findings where the turning point for average irrigation times

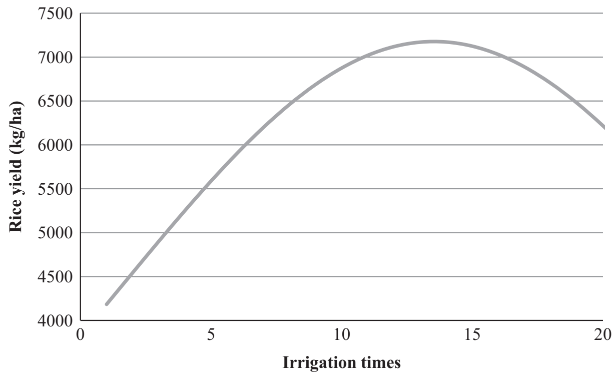

Figure 1 Nonlinear effects of irrigation times on rice yield.

in South China was 10, but under water-catching and controlled irrigation (Guo *et al.* 2009).

Figure 1 presents the partial effect of irrigation on rice yield, which clearly shows the nonlinear effect of irrigation. We find that below 13 irrigation times, yield increases nonlinearly with irrigation, such that an increase in the number of irrigation times by 1 from 3 to 4 increases the mean rice yield by 0.094, but an increase from 4 to 5 raises the mean rice yield by 0.080, holding other variables constant. When evaluated at sample means, each one increase in irrigation times on average increases the mean rice yield by 0.063.

As shown in Table 4, other estimated coefficients are also statistically significant with expected signs. For example, the impact of drought on rice yield is significant and negative and thus may increase the production risk. We also find positive and significant impacts of conventional input variables —labour and machinery—on rice yield. The estimated elasticity of labour and machinery is approximately 0.07 and 0.02, respectively. These results are consistent with the previous findings (e.g. Holst *et al.* 2013; Huang *et al.* 2015). In addition, we show that the wealthier the farmer, the higher their rice yield.

5.3 Impacts on production risk

Following Kim and Chavas (2003), we first test whether or not the yield distribution is symmetrically distributed using a Wald statistic. If the null hypothesis of symmetry is rejected, this constitutes evidence that the distribution of yield is skewed to the left, corresponding to a significant exposure to downside yield risk (Koundouri *et al.* 2006). The mean skewness of u is -0.22 and the Wald statistic is statistically different from zero, with a P-value of 0.00. We therefore reject the null hypothesis of symmetry in the yield distribution owing to skewness.

Table 5 shows that the coefficients of both the linear and quadratic terms of irrigation times are statistically significant in the variance function

Table 5 Econometric estimates of variance and skewness of yield

Variables	(1) Variance (log)	(2) Skewness
Irrigation times	−0.50*** (0.13)	0.19* (0.10)
Irrigation times square	0.02*** (0.01)	−0.01** (0.00)
Drought (1 = yes, 0 = no)	0.34** (0.14)	−0.05 (0.11)
Inputs		
Labour (log)	−0.04 (0.11)	0.04 (0.09)
Machinery (log)	−0.02 (0.02)	−0.01 (0.01)
Fertiliser (log)	−0.07 (0.08)	−0.10* (0.06)
Other inputs (log)	−0.00 (0.04)	0.02 (0.03)
Drought-tolerant variety	−0.02 (0.09)	0.06 (0.07)
Farm characteristics		
Primarily male labour, engaged mainly in farming (yes = 1, no = 0)	−0.24 (0.15)	0.25** (0.12)
Primarily female labour, engaged mainly in farming (yes = 1, no = 0)	0.28 (0.18)	−0.16 (0.14)
Age of household head	−0.01** (0.01)	−0.00 (0.00)
Education of household head	−0.01 (0.02)	−0.00 (0.01)
Land per capita (ha)	0.10 (0.08)	−0.03 (0.06)
Durable consumption assets (10,000 yuan)	−0.02 (0.03)	0.03 (0.02)
Plain land (yes = 1, no = 0)	0.26 (0.19)	0.11 (0.15)
Loam soil (yes = 1, no = 0)	−0.29** (0.14)	−0.06 (0.11)
Clay soil (yes = 1, no = 0)	−0.31*** (0.12)	−0.07 (0.10)
Saline soil (yes = 1, no = 0)	0.29 (0.22)	−0.21 (0.17)
Crop dummies (base is early-season rice)		
Middle-season rice	0.14 (0.16)	0.21 (0.13)
Late-season rice	0.21 (0.13)	−0.19* (0.10)
Constant	−2.12* (1.18)	0.70 (0.95)
Year dummies	Yes	Yes
Province dummies	Yes	Yes

Notes: Both regressions are weighted by the ratio of village population (in terms of number of households) to county population. The robust standard errors, clustered at the village level, are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The sample is 2,898 (1,449 × 2 years).

(Table 5). The negative linear term and positive quadratic term imply that irrigation reduces yield variance, but only below a certain irrigation level. We find that irrigation increases the variance when the number of irrigation times is above 12. When evaluated at sample means, an increase in irrigation times of 1 is associated with a 0.198 decrease in yield variance. With respect to the estimations of the yield skewness function, the coefficient of the linear term for irrigation times is positive, whereas the coefficient of the quadratic term is negative. This indicates that irrigation can reduce downside exposure (i.e. increase skewness), but only below a certain application of irrigation. When evaluated at sample means, the marginal impact of irrigation on skewness is 0.068. Thus, our results indicate that suitable levels of irrigation can be very effective in reducing farmers' exposure to downside risk.

Drought is positively related to both production risk exposure and downside risk, but the effect is statistically significant only for the variance function (Table 5). Fertiliser use is found to have a significantly negative effect on yield skewness. This implies that fertiliser is a risk-increasing input, which is consistent with the previous findings (e.g. Abedullah and Pandey 2004; Finger *et al.* 2011). The age of the household head is negatively associated with both risk exposure and downside risk, and the effect is statistically significant only for the variance function. This is because older farmers generally have more farming experience or of the use of technologies in production practice, and thereby have better management abilities when it comes to production risk. The coefficients associated with soil condition are negatively related to risk exposure. This implies that farmers with better soil quality are less exposed to production risk.

6. Concluding remarks

Given the increasing crisis of drought under climate change, even in traditional rice-growing areas, where the surface water for irrigation is generally abundant, adaptive irrigation management is relevant. Based on field survey data from rice farms in China, this paper presents an empirical analysis of the role of local irrigation infrastructure in improving farmers' ability to respond to drought by changing irrigation, and therefore its effectiveness in mitigating drought risk.

We find that extreme drought increases the vulnerability of rice production in our study areas. Drought shock significantly reduces rice yield and increases production risk. Our analysis also shows that farmers' adaptive irrigation can play a beneficial role both in supporting rice yield and in managing drought risk. According to our estimation, when evaluated at sample means, an increase in irrigation times by 1, on average, increases the mean rice yield by 0.063 and decreases the risk and downside risk by 0.198 and 0.068, respectively. Hence, we stress the role of irrigation as a strategy for adaptive risk management in agriculture in the context of climate change. The strategy can indeed buffer against extreme drought and play a crucial role in reducing the food insecurity of farm households. Furthermore, empirical evidence highlights that local irrigation infrastructure has a major role in supporting this response. We find that farmers in villages with good infrastructure increase their irrigation times sharply in response to drought.

In terms of policies to support the adaptive response by farmers, our findings suggest that there is value for government to consider investment in irrigation infrastructure, such as shoring up small reservoirs and building new systems. For this purpose, investment in irrigation infrastructure could be incorporated as an option in China's national climate change adaptation strategy. If an investment is made, then attention to the management and maintenance of the infrastructure is also important.

Outside of China, the results of our study can be used to inform policymakers looking to design their own agricultural adaptation plan in coping with drought. In many developing countries, under the context of climate change, water shortages and underinvestment in irrigation infrastructure are still common. We have shown that strengthening irrigation infrastructure is crucial to improving the availability of irrigation and farmers' adaptive capacity against drought risk. This could provide policy decision evidence for other developing countries in determining the investment priority of the national or local climate change adaptation plan design.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Table A1:Descriptive statistics of variables.