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# The adoption and impact of engineering-type measures to address climate change: evidence from the major grain-producing areas in China\*

Chunxiao Song, Ruifeng Liu, Les Oxley and Hengyun Ma<sup>†</sup>

Employing an endogenous switching regression model, we investigate the drivers underlying the adaptations made by farm households and their impacts on crop net incomes for adopters and nonadopters, based on a large panel survey data set across the major grain-producing provinces in China. The results show that: (i) access to public climate information and technical or physical support increases the likelihood that farmers adapt to climate change by undertaking irrigation and/or drainage measures; and (ii) decisions to adapt increased crop yield, but they did not significantly increase crop profit margins. This point appears to have been ignored by previous studies. Based on these new empirical results, the paper suggests that government should continue to provide climate information and various types of supports to improve farmers' adaptation abilities and help to reduce the levels of factor input by, for example, substituting organic for chemical fertiliser inputs. Such government-led policies should be supported alongside the implementation of domestic agricultural supply-side reform.

**Key words:** China, crop net income, crop yield, engineering adaptive measures, extreme weather events, long-term climate change.

## 1. Introduction

With long-term climate change and rising extreme weather events, agricultural production is becoming more volatile with farmers potentially facing crop losses and threats to their livelihood (IPCC 2014). For example, flood damage costs worldwide have increased since the 1970s and the total area suffering from drought globally is forecast to increase by between 15 per cent and 44 per cent by the end of the 21<sup>st</sup> century (IPCC 2012). In China, the predicted grain losses due to drought is estimated to be 16.23 million tonnes annually, accounting for 4.16 per cent of total grain output (CFDB 2012; CSY 2012), which exceeds the calculated contribution of technological progress (Chen *et al.* 2008).

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To alleviate the effect of climate change on agricultural production and farmers' income, some adaptive measures have been adopted to reduce climate risk and vulnerability. Many researchers have analysed the impact of future climate outcomes on crop production using cropping system simulation models and explored the advantages of specific adaptive strategies under different simulation scenarios. Their results indicate that crop yields would decline if faced with realistic future climate change, but also that the adoption for appropriate adaptive measures could offset this yield loss and even (potentially) increase crop yields (Babel and Turyatunga 2015; Deb *et al.* 2016).

Most of these studies have focused on the factors that constitute the barriers to farmers opting for adaptations to climate change (Bryan *et al.* 2009; Deressa *et al.* 2009; Gbetibouo *et al.* 2010; Yegbemey *et al.* 2013; Chen *et al.* 2014; Wang *et al.* 2014a), rather than investigating the reasons why some farmers adapt to climate change (Di Falco *et al.* 2011; Huang *et al.* 2015; Asfaw *et al.* 2016) and what effect this has on crop net income. However, there are a few studies that investigate the behaviour of engineering adaptive measures at the farm level (Wang *et al.* 2014a, 2017) using profit function instead of yield function as the measure of the success of these adaptations. It is interesting to find that using a profit function as the measure of successful adaption generates different policy conclusions than using a yield function because Chinese farmers concentrate more on profit margins.

To fill these gaps in the literature, this study focuses on *the effect on farmers' crop 'net income' of adopting 'engineering-type adaptive measures'*, in particular, what factors determine which type of adaptive measures are adopted? Here, we treat irrigation and drainage engineering measures as 'adaption' and employ an endogenous switching regression model (*ESRM*) to analyse the driving forces behind farm households (HHs) decisions to adapt to climate change. We examine how the decision to adapt impacts upon crop net income, using a large panel survey data set 2010–2012 across five major grain-producing provinces in China.

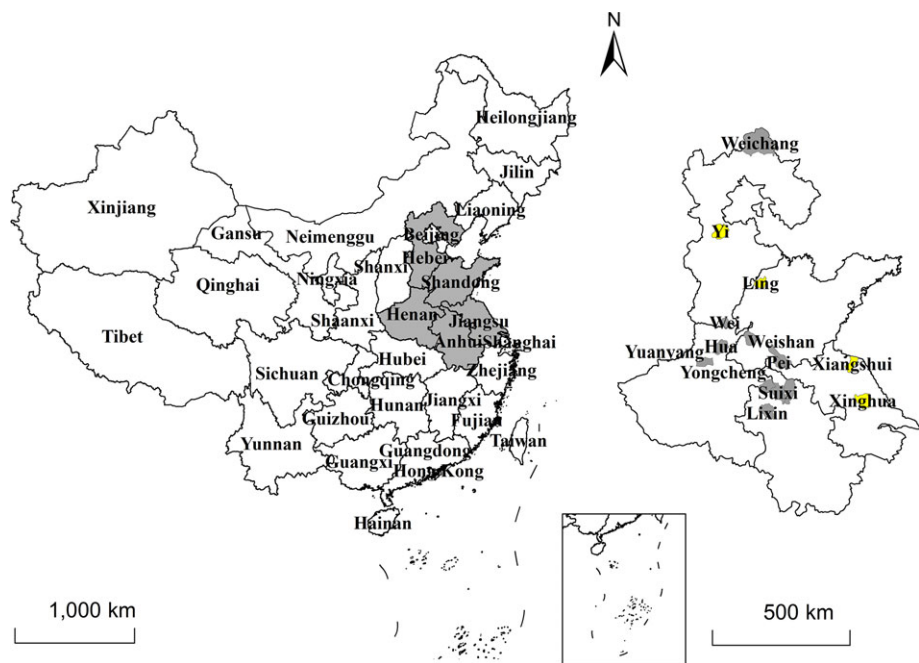
The rest of this paper is organised as follows: Section 2 briefly introduces the sampling procedure and describes the data set. Section 3 discusses a switching regression model of engineering adaptive measures and crop income. Section 4 describes the empirical model and variables. The estimation results are presented in Section 5, and the final section concludes the paper with some policy suggestions.

## 2. Sample and variable selection

### 2.1 Sampling procedure

The data used in this study are mainly taken from a large-scale field survey across five grain-producing provinces in China (Figure 1). The survey was conducted from the end of 2012 through to early 2013. From each of the provinces selected, three counties were randomly chosen using a criterion

meeting the following two conditions: (i) the counties experienced at least one episode of either severe drought or flood between 2010 and 2012 and (ii) the counties experienced at least one normal year in the past 3 years (2010, 2011 or 2012). According to China's national standard for natural disasters (CMA 2004), the severity of a drought or flood has four categories: most severe; severe; moderate; and small. If the Government declares a disaster warning and the level is the most severe or severe, we consider it a disaster year. Crop production often faces various weather shocks during any growing seasons; the term 'normal year' is relative and describes an average year with no more than moderate weather shocks. Table 1 indicates that 11 counties experienced severe drought in 2011 and relatively normal in 2012, three counties experienced severe flood in 2012 and relatively normal in 2011, and one county experienced severe flood in 2011 and relatively normal in 2012. Then, from each of the chosen counties, three townships were randomly selected and they must also meet the 'good', 'medium' and 'poor' local irrigation and drainage infrastructure conditions, respectively. Similarly, three villages were randomly selected from each township, and 10 HHs were randomly selected for face-to-face interviews from each village. From each HH, two plots with grain production were randomly selected. For further details on the sampling procedure, see Wang *et al.* (2017). The data used in this paper are from the same source as Wang *et al.* (2017). The final sample came from five provinces, 15 counties, 45 townships, 135 villages, 1,350 HHs and 2,700 plots. For this



**Figure 1** Location of five provinces in China (left) and 15 counties in provinces (right). [Colour figure can be viewed at [wileyonlinelibrary.com](#)].

**Table 1** The distribution of sample households (HHs) and plots across five provinces

Province	County	Number of HHs	Number of plots	Disaster/year
Henan	Yuanyang	90	167	D/2011
	Huaxian	90	159	D/2011
	Yongcheng	90	176	D/2011
Hebei	Weixian	90	164	D/2011
	Yixian	89	160	F/2012
	Weichang	90	173	D/2011
Shandong	Lingxian	90	171	F/2012
	Yuncheng	89	174	D/2011
	Weishan	90	163	D/2011
Jiangsu	Xinghua	90	178	F/2011
	Xiangshui	90	180	F/2012
	Peixian	90	180	D/2011
Anhui	Yongqiao	90	175	D/2011
	Suixi	90	172	D/2011
	Lixin	90	177	D/2011
Total	15	1,348	2,569	—

Note: D indicates the severe drought year; and F indicates the severe flood year.

study, we include 1,348 HHs and 2,569 plots. The other data were excluded due to incomplete records. The sample distribution is shown in Table 1, which indicates Henan Province is located in central China, Hebei in northern, Shandong and Jiangsu in eastern coastal areas, and Anhui in inland eastern.

## 2.2 Variable assumptions

### 2.2.1 Target variables

The engineering measures we use include irrigation and drainage engineering facilities such as pumps, irrigation/drainage ditches, motor-pumped wells and others, which were built or repaired in 2010–2012. It can be seen that more farm HHs applied engineering adaptive measures in a disaster year than in a normal year. Approximately 21 per cent of farm HHs bought or repaired their pumps, 15–16 per cent of farm HHs dug or maintained irrigation/drainage ditches, 6.7 per cent invested or maintained motor-pumped wells for irrigation, and a few (1 per cent) invested in other engineering measures (Table 2).

The engineering measures, as long-term irrigation and drainage services, need to be regularly rebuilt and repaired. That is, building and repairing in engineering measures do not necessarily represent true adaptations. However, to distinguish whether building or repairing engineering facilities belongs to adaptive measures, we considered two cases: Firstly, building or repairing behaviour is considered to be an adaptive measure when it occurred during the disaster years. Secondly, during the face-to-face field interviews, we asked farmers whether they undertook adaptive measures in a drought/flood year or in relation to long-term climate change.

**Table 2** Percentages of farm households taking engineering adaptation measures in disaster year and normal year (%)

Year	Total	Pumps	Irrigation/drainage ditches	Motor-pumped wells	Others
Disaster year	35.5	21.1	16.0	6.9	1.0
Normal year	38.2	19.8	15.0	6.5	1.1
Average	36.9	20.5	15.5	6.7	1.0

Crop yield is measured as ‘crop output per hectare’, which is calculated from the total crop output of each plot divided by the plot area (hectare). A similar transformation is used for ‘crop net income’, which is defined as crop gross value (price times yield per hectare) minus total physical input costs and hired labour inputs per hectare. The physical inputs include fertiliser, pesticides, seeds, manure, machinery and others. The average difference between adopters and nonadopters is 805.24 kg/ha in terms of crop yield and 1,700 yuan/ha in terms of crop net income. The results of *t*-tests suggest significant differences in crop yield and crop net income between adopters and nonadopters (Table 3, rows 2 and 3).

2.2.2 *Exogenous variables*

It appears that there are significant differences between adopters and nonadopters in terms of the public climate information service and public physical support policy utilised, showing that more adopters have received information and support than nonadopters (Table 3, rows 4 and 5).

First, consider the *public climate information service*. It is measured as the access to the public climate warning and prevention information against disaster through various dissemination channels such as television, broadcast, text messages released by the meteorological station, agro-technical station and urgent disaster documents issued by different levels of Government in this paper. Chen *et al.* (2014) and Wu and Liu (2015) found that drought and flood warnings, and prevention information would impact upon the adaptation behaviour of HHs. It is expected that those HHs who heard or read about climate information are more likely to take up adaptation measures and those who lacked information did not undertake any adaptation actions. Therefore, many researchers suggest that it is imperative to solve the lack of climate forecasts at the local level (Di Falco *et al.* 2011; Tambo and Abdoulaye 2012; Comoé and Siegrist 2015).<sup>1</sup>

<sup>1</sup> When information provided before a disaster occurs, it mainly emphasises how to prevent potential losses by telling farmers the possible duration and seriousness of the forecasted disaster and by reminding farmers that they should take appropriate adaptation measures to reduce losses. When information provided during or after the disaster, it is mainly to help farmers use remedial measures to minimise grain production losses.



**Table 3** Descriptive tests of variables by adopters and nonadopters of engineering measures

Variables	Adopters	Nonadopters	Diff.	t-Value
Target variables				
Crop yield (kg/ha)	12,377.93	11,572.69	805.24***	7.67
Crop net income (10 <sup>3</sup> yuan/ha)	15.44	13.75	1.70***	8.08
Exogenous variables				
Access to govt climate info against disaster (1 = yes; 0 otherwise)	0.12	0.08	0.05***	5.70
Access to govt tech., material or financial supports against disaster (1 = yes; 0 otherwise)	0.39	0.26	0.14***	10.40
Exposure to climate change				
Mean of temperature in 1983–2012 (°C)	14.33	12.95	1.39***	15.87
Mean of precipitation in 1983–2012 (mm)	797.60	676.31	121.29***	24.73
If severe drought year (1 = yes; 0 otherwise)	0.33	0.39	−0.05***	−3.75
If severe flood year (1 = yes; 0 otherwise)	0.19	0.10	0.08***	8.27
Input factors				
Fertiliser cost (yuan/ha)	5,154.32	4,808.25	346.06***	5.68
Pesticide cost (yuan/ha)	1,153.97	782.51	371.46***	17.02
Total machinery cost (yuan/ha)	2,944.57	2,624.30	320.27***	8.51
Total labour (adult days/ha)	105.85	97.94	7.91***	2.89
Village irrigation and drainage condition				
If irrigation and drainage infrastructures (1 = yes; 0 otherwise)	0.97	0.94	0.03***	5.31
HH characteristics				
The durable goods of HH (10 <sup>3</sup> yuan)	11.16	9.92	1.24**	2.19
Agricultural income (% of agri. income in total)	47.75	47.36	0.40	0.29
Producing/technical training (1 = yes; 0 otherwise)	0.45	0.23	0.22***	17.07
Gender of HH head (1 = male; 0 otherwise)	0.960	0.956	0.004	0.63
Education of HH head (year)	7.01	6.85	0.16*	1.71
Farming experience of HH head (year)	35.88	34.92	0.96***	2.93
Farmland characteristics				
Farmland area (ha)	0.20	0.20	0.004	0.83
Farmland types (1 = plain; 0 otherwise)	0.97	0.89	0.08***	10.64
If farmland is transferred (1 = yes; 0 otherwise)	0.06	0.05	0.01*	1.69
If sand or not (1 = yes; 0 otherwise)	0.283	0.279	0.004	0.32
If loam or not (1 = yes; 0 otherwise)	0.32	0.33	−0.01	−0.65
If clay or not (1 = yes; 0 otherwise)	0.394	0.389	0.005	0.34

Note: \*, \*\* and \*\*\* represent significance 10%, 5% and 1% level, respectively.

Second, consider *public physical support policy*. This is measured as the technical, material or financial policy support against disasters received from the Government. Policy support from local government and national and international organisations has been shown to be relevant and facilitated farmers' adaptation decision-making with regard to climate change (Bryan *et al.* 2009; Deressa *et al.* 2009; Gbetibouo *et al.* 2010; Tambo and Abdoulaye 2012; Wang *et al.* 2014b; Huang *et al.* 2015; Asfaw *et al.* 2016).

### 2.2.3 Climate change

The first indicators are long-term climate change, including mean of temperature and precipitation in 1983–2012. Many studies have investigated the effect of climate change on the behaviour of farmers' adaptation to long-term climate change. For example, Deressa *et al.* (2009) found that farmers would undertake more adaptation methods when experiencing rising temperature and declining precipitation. Seo *et al.* (2008) found that African farmers would also adopt different adaptive measures under different weather scenarios in future. Arslan *et al.* (2014) found a positive relationship between the use of conservation agriculture and weather variability. However, Bryan *et al.* (2009) suggested that when farmers were asked about adaptations to long-term climate change in average temperature and rainfall conditions, their behaviour depends more on short-term climate variations and extremes.

The second measures are of extreme weather events. Many studies have found that farmers take various measures to adapt extreme weather events (e.g. Habiba *et al.* 2012; Chen *et al.* 2014; Huang *et al.* 2014, 2015; Wang *et al.* 2014a). Huang *et al.* (2015) found that natural disasters had significantly negative effects on the rice yield and that severe floods and drought encourage farmers to improve farm management. Di Falco *et al.* (2011) and Asfaw *et al.* (2016) found that greater variability in rainfall and maximum temperature during the growing season would increase the use of risk-reducing practices, and a late onset of the rainy season negatively and significantly affects the value of production, indicating that the adaptive behaviour makes the farmers who adapted more resilient to cope with climate change during the most important rainfall season compared with non-adopters.

### 2.2.4 Input factors

Adopters are more likely to use more production inputs than nonadopters. The average inputs of fertiliser, pesticide, machinery and total labour are 346.06 yuan, 371.46 yuan, 320.27 yuan and 7.91 adult days per hectare more, respectively, for adopters than for nonadopters and that these differences are significant (Table 2, rows 9–12). Alene and Manyong (2007) and Di Falco *et al.* (2011) also found that most of the production inputs are significantly associated with increasing crop production, but there are different effects on outcomes between adopters and nonadopters.

### 2.2.5 Village irrigation and drainage condition

The condition of irrigation and drainage in the village is measured if there is any irrigation and drainage infrastructure, and the *t*-values show that there is significant difference in village infrastructure between adopters and nonadopters. Wang *et al.* (2014a) and Wu and Liu (2015) found that better village irrigation and drainage infrastructure



significantly and negatively affect the probability HHs take physical adaptation measures.

#### 2.2.6 *The HH characteristics*

The assets owned by the HHs are measured as the value of durable goods, which is an oft-cited factor explaining differential rates of adaptation. This suggests that wealthier HHs are more likely to adapt to climate change and are better able to offset climate risk than poor HHs (Bryan *et al.* 2009; Comoé and Siegrist 2015).

The higher the proportion of agricultural income (as a share of total income) means farm HHs give more attention to crop production and would rather adopt measures to reduce risk and assure crop yield when climate changes. If the proportion of farm income is low, it means farmers earn most of the money from engaging in nonfarm activities, which may restrict the allocation of labour to farm activities and negatively impact on adaptive measures (Abdulai and Huffman 2014).

Production and technique training are the best ways of obtaining new productive technologies, which could be used to improve farmers' adaptation to climate change and increase crop yield (Hussain *et al.*).

The effects of HH head on adaptation area are priori ambiguous. Deressa *et al.* (2009) argued that male HH heads are more likely to adopt measures to negate climate change, while Nhemachena and Hassan (2007) found that female-headed HH are more willing to take adaptive measures.

Education is expected to be one of the most important factors related to agricultural productivity. In fact, many studies have found it has a positive impact on technological adoption (Teklewold *et al.* 2013; Asfaw *et al.* 2016). Furthermore, Alene and Manyong (2007) and Abdulai and Huffman (2014) concluded that education not only enhances agricultural productivity following adoption but also promotes adoption itself.

Similarly, experienced farmers who are highly skilled in farming techniques and management are able to spread risk when facing climate variability by exploiting strategic complementarities between activities (Gbetibouo *et al.* 2010).

#### 2.2.7 *Farmland characteristics*

Farmland characteristics are captured through farm size, farm type, whether the farmland is owned or leased/rented, and soil type. Farm size is hypothesised to affect on farmers' adaptation and crop yields. Abdulai and Huffman (2014) concluded that farm size has significant positive effects on farmers' willingness to undertake adaptive measures. However, Asfaw *et al.* (2016) argued that total land holdings are negatively correlated with the adaptation measures such as the use of organic fertiliser and modern inputs. Furthermore, there is a strong negative correlation between farm size and crop yields, in that the higher yields observed in small farms are mainly

attributed to higher factor inputs and to a more intensive use of land (Carter 1984; Cornia 1985).

Here, farmland type is measured as plain plot, or gentle slope, steep slope and hilly plot. Abdulai and Huffman (2014) found that farmers are more likely to construct bunds on land with steep slopes to slow down water flow and reduce soil erosion, and Wu and Liu (2015) noted that farmers are more likely to adopt engineering measures like ditching to cope with floods if the plot is in a hilly area as drainage is more difficult and it is more vulnerable to catastrophic disaster on the steeper land.

Whether the farmland is owned or leased/rented is important. During the implementation of the *HH Responsibility System*, most arable land in rural China was evenly allocated to each farm HH, which resulted in the formation of tiny plots and scattered planting. When rural labour move to urban areas, associated farmland is poorly managed. As a result, land rental markets began developed and the untended land plots transferred to farm HHs with the capability to expand their operations (Deininger and Jin 2005).

Soil characteristics are found to play a crucial role in decision-making and mainly influence farmers' adaptation to climate change because there are significant variations in productivity across the types of soil and the farm HHs have to decide which types of soil are worth of investing irrigation and drainage engineering measures (Teklewold *et al.* 2013; Asfaw *et al.* 2016).

Although the comparisons discussed above reveal some significant differences between adopters and nonadopters, the differences are not sufficient to explain the relationship between adaptation and crop yield and crop net income across HHs. Therefore, in the next section, we attempt to ascertain the driving forces for farm HHs who undertook engineering adaptive measures by modelling adaptation as a selection process.

### 3. Switching regression model

Table 3 showed significant differences in crop yield and crop net income between adopter and nonadopter HHs. Such differences identified in Table 3, however, simply consider each variable in isolation. To consider potential interactions between variables and to identify the relative size of effects of each variable, we next consider a regression model of yield and crop net income. The model contains engineering adaptive measures as a treatment variable and controls for other variables (Lokshin and Sajaia 2004). Attempts to measure the impact of farm HH engineering adaptive measures on crop yield or crop net income are hampered by the fact that the 'before' and 'after' activities of farm plots are rarely observed. Instead, researchers are usually left to compare adopters with nonadopters (Fuglie and Bosch 1995). However, the decision to adopt engineering measures is voluntary, and it may lead to sample selection bias (Hausman 1978). For example, farmers with more skills and abilities are more likely to be those who are also adopting the technologies and vice versa. To solve this

problem, we utilise an *ESRM* here to control for both observed heterogeneity and unobserved heterogeneity, and estimate two separately, but related crop yield or crop net income equation for adopter or nonadopter, respectively, in combination with a selection equation (Alene and Manyong 2007; Kassie *et al.* 2010; Di Falco *et al.* 2011; Rao and Qaim 2011; Kabunga *et al.* 2012; Abdulai and Huffman 2014; Huang *et al.* 2015).

### 3.1 The endogenous switching regression model

The paper uses *ESRM* to model the engineering adaptation decision-making to climate change and its impact on crop yield and crop net income. Specifically, it is modelled in the setting of a two-stage framework. In the first stage, the model uses a probit regression to determine the relationship between each adaptation and the possible determinants of adaptation; in the second stage, separate regression equations for each group (adopters and nonadopters) are used to model outcome conditional on a specified criterion function (Lee 1978).

In the first stage, consider the following model, let  $A_i^* > 0$  be the latent variable capturing the expected benefits from adaptation choice with respect to not adapting. We specify the latent variable as:

$$A_i^* = \mathbf{Z}_i \boldsymbol{\alpha} + \mu_i \text{ with } A_i = \begin{cases} 1 & \text{if } A_i^* > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$

where farmland plot  $i$  will be chosen to adapt by HH ( $A_i = 1$ ), through the implementation of engineering measures in response to long-term climate change and extreme weather events.  $\mathbf{Z}_i$  is a vector of factors influencing adaptation to climate change.  $\boldsymbol{\alpha}$  is a vector of parameters, and  $\mu_i$  is an error term where  $\mu_i \sim N(0, \sigma_\mu^2)$ . Probit maximum likelihood estimation method is employed to estimate the parameters of Equation (1).

In the second stage, the outcome function can be defined as  $Y = f(\mathbf{X})$ , where  $Y$  is either crop yield or crop net income and  $\mathbf{X}$  is a vector of factors that influences outcome. Given that the choice to apply engineering adaptation measures lies with the farmers, a separate regression function is specified for adopters and nonadopters:

$$\text{Regime 1 (Adopters)} : Y_{1i} = \mathbf{X}_{1i} \boldsymbol{\beta} + \varepsilon_{1i} \quad \text{if } A_i = 1, \quad (2a)$$

$$\text{Regime 2 (Nonadopters)} : Y_{2i} = \mathbf{X}_{2i} \boldsymbol{\beta}' + \varepsilon_{2i} \quad \text{if } A_i = 0, \quad (2b)$$

where  $Y_{1i}$  and  $Y_{2i}$  are outcome variables for the adopters and nonadopters, respectively. Since the choice of engineering measures is endogenous, ordinary least squares estimates of the vectors  $\boldsymbol{\beta}$  and  $\boldsymbol{\beta}'$  will suffer from sample selection

bias: the error terms in Equations (2a) and (2b), conditional on the sample selection criterion, have nonzero expected values (Lee 1978).

The three error terms  $\mu$ ,  $\varepsilon_1$  and  $\varepsilon_2$  in Equations (1), (2a) and (2b) are assumed to have a trivariate normal distribution with mean vector zero and covariance matrix:

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

where  $\text{Var}(\mu) = \sigma_\mu^2$ ,  $\text{Var}(\varepsilon_1) = \sigma_1^2$ ,  $\text{Var}(\varepsilon_2) = \sigma_2^2$ ,  $\text{Cov}(\mu, \varepsilon_1) = \sigma_{\mu 1}$ ,  $\text{Cov}(\mu, \varepsilon_2) = \sigma_{\mu 2}$ , and  $\text{Cov}(\varepsilon_1, \varepsilon_2) = \sigma_{12}$ . Note that  $Y_{1i}$  and  $Y_{2i}$  are not observed simultaneously, which means that the covariance between  $\varepsilon_1$  and  $\varepsilon_2$  is not defined. Since the error term of the selection Equation (1) is correlated with the error terms of the outcome functions (2a) and (2b), the expected values of the error terms  $\varepsilon_1$  and  $\varepsilon_2$ , conditional on the sample selection, are nonzero and are given as follows:

$$E[\varepsilon_{1i}|A_i = 1] = \sigma_{1\mu} \frac{\varphi(\mathbf{Z}_i\boldsymbol{\alpha})}{\phi(\mathbf{Z}_i\boldsymbol{\alpha})} = \sigma_{1\mu}\lambda_{1i}, \quad (3a)$$

$$E[\varepsilon_{2i}|A_i = 0] = -\sigma_{2\mu} \frac{\varphi(\mathbf{Z}_i\boldsymbol{\alpha})}{1 - \phi(\mathbf{Z}_i\boldsymbol{\alpha})} = \sigma_{2\mu}\lambda_{2i}, \quad (3b)$$

where the standard normal probability density function is  $\varphi(\cdot)$  and  $\phi(\cdot)$  is the normal cumulative distribution function. The terms  $\lambda_1$  and  $\lambda_2$  refer to the inverse Mills ratio evaluated at  $A_i^* = \mathbf{Z}_i\boldsymbol{\alpha} + \mu_i$  (Greene 2003) and are incorporated into Equations (2a) and (2b) to account for sample selection bias, and  $\lambda_1 = (\varphi(\mathbf{Z}_i\boldsymbol{\alpha})/\phi(\mathbf{Z}_i\boldsymbol{\alpha}))$ ,  $\lambda_2 = -((\varphi(\mathbf{Z}_i\boldsymbol{\alpha}))/ (1 - \phi(\mathbf{Z}_i\boldsymbol{\alpha})))$ , respectively.

Here, we used the full information maximum likelihood (FIML) method to estimate the *ESRM*, which is more efficient than the two-step least squares and maximum likelihood methods (Lokshin and Sajaia 2004). Given the assumption of trivariate normal distribution for the error terms, the logarithmic likelihood function can be given as follows:

$$\ln L_i = \sum_{i=1}^N \{A_i \left[ \ln \varphi \left( \frac{\varepsilon_{1i}}{\sigma_1} \right) - \ln \sigma_1 + \ln \phi(\theta_{1i}) \right] + (1 - A_i) \left[ \ln \varphi \left( \frac{\varepsilon_{2i}}{\sigma_2} \right) - \ln \sigma_2 + \ln(1 - \phi(\theta_{2i})) \right] \}, \quad (4)$$

where  $\theta_{ji} = (\mathbf{Z}_i + \rho_j \varepsilon_{ji}/\sigma_j)/(\sqrt{1 - \rho_j^2})$ ,  $j = 1, 2$ , with  $\rho_j$  denoting the correlation between the error term  $\mu_i$  of the selection Equation (1) and the error term  $\varepsilon_{ji}$  of Equations (2a) and (2b), respectively.  $\rho_{1\mu} = (\sigma_{1\mu})/(\sigma_1\sigma_\mu)$  is the coefficient of correlation between  $\mu$  and  $\varepsilon_1$  and  $\rho_{2\mu} = (\sigma_{2\mu})/(\sigma_2\sigma_\mu)$  is the

coefficient of correlation between  $\mu$  and  $\varepsilon_2$ . The estimated  $\rho_{1\mu}$  and  $\rho_{2\mu}$  are bounded between  $-1$  and  $1$ , and the estimated  $\sigma_1$  and  $\sigma_2$  are always positive.

It is noteworthy that if the coefficient of correlation  $\rho_{1\mu}$  and  $\rho_{2\mu}$  are statistically significant, such that the decision to adapt and the outcome are correlated. This implies that there is evidence of endogenous switching and the null hypothesis indicating the absence of sample selectivity bias is rejected (Abdulai and Huffman 2014; Akpalu and Normanyo 2014). The signs of the correlation coefficients  $\rho_{1\mu}$  and  $\rho_{2\mu}$  have economic interpretation. If  $\rho_{1\mu}$  and  $\rho_{2\mu}$  have alternate signs, then farm HHs take engineering adaptive measures on the basis of their comparative advantage: those who adopt have above-average returns from adoption and those who choose not to adopt have above-average returns from nonadoption. On the other hand, if the coefficients have the same sign, it indicates hierarchical sorting: adopters have above-average returns whether they adopt or not, but they are better off adopting, whereas nonadopters have below-average returns in either case, but they are better off not adopting (Fuglie and Bosch 1995; Alene and Manyong 2007). Moreover,  $\rho > 0$  indicates negative selection bias, suggesting that farm HHs with below-average outcome are more likely to take engineering adaptive measures; on the contrary,  $\rho < 0$  implies positive selection bias, indicating that farm HHs with below-average outcomes have a higher likelihood to adapt (Rao and Qaim 2011; Kabunga *et al.* 2012; Abdulai and Huffman 2014).

### 3.2 Conditional expectations and treatment

The *ESRM* can be used to compare the observed and counterfactual outcome. In the actual expectations observed case, the expected outcome function for an adopter, if the farm HHs adopted the engineering measures and the expected outcome function for a nonadopter if the farm HHs did not adopt engineering measures, can be defined as Equations (5a) and (5b):

$$E(Y_{1i}|A_i = 1) = \mathbf{X}_{1i}\boldsymbol{\beta} + \sigma_{1\mu}\lambda_{1i}, \quad (5a)$$

$$E(Y_{2i}|A_i = 0) = \mathbf{X}_{2i}\boldsymbol{\beta}' + \sigma_{2\mu}\lambda_{2i}. \quad (5b)$$

While, in the counterfactual hypothetical cases, Equation (5c), the expected outcome function for the same adopter who had chosen not to adopt engineering measures and, Equation (5d), the expected outcome function for the same nonadopter who had chosen to adopt engineering measures can be defined as follows:

$$E(Y_{2i}|A_i = 1) = \mathbf{X}_{1i}\boldsymbol{\beta}' + \sigma_{2\mu}\lambda_{1i}, \quad (5c)$$

$$E(Y_{1i}|A_i = 0) = \mathbf{X}_{2i}\boldsymbol{\beta} + \sigma_{1\mu}\lambda_{2i}. \quad (5d)$$

Following Heckman *et al.* (2001), Di Falco *et al.* (2011) and Akpalu and Normanyo (2014), the change in outcome for the adoption of engineering measures can then be specified as the difference between adoption and nonadoption. To estimate the adaptation's net effect on crop yield and crop net income, some further calculations are required. The effect of the average treatment on the treated (ATT) is calculated as the difference between (5a) and (5c), which represents the effect of climate change adaptation on the crop yield and crop net income of the farm HHs that actually adapted to climate change, and is given by Equation (6a). Similarly, the effect of the average treatment on the untreated (ATU) is calculated as the difference between (5d) and (5b), which represents the effect of climate change adaptation on the crop yield and crop net income of HHs that actually did not adapt to climate change, which is given by Equation (6b). These expected outcomes can be used to derive unbiased treatment effects ATT and ATU that control for observed and unobserved heterogeneity (Wooldridge 2010):

$$ATT = E(Y_{1i}|A_i = 1) - E(Y_{2i}|A_i = 1) = \mathbf{X}_{1i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_0) + (\sigma_{1\mu} - \sigma_{2\mu})\lambda_{1i}, \quad (6a)$$

$$ATU = E(Y_{1i}|A_i = 0) - E(Y_{2i}|A_i = 0) = \mathbf{X}_{1i}(\boldsymbol{\beta}_1 - \boldsymbol{\beta}_0) + (\sigma_{1\mu} - \sigma_{2\mu})\lambda_{2i}. \quad (6b)$$

As to sampling representativeness and sampling weight, the selection scheme (highly stratified sample) did not use probabilities proportional to size, in effect neglecting the different sizes across villages. In order to solve this problem, all regressions are weighted by the ratio of village population to county population (Wang *et al.* 2017). In addition, following Huang *et al.* (2015), we clustered the standard errors at the household level and used the Huber/White/sandwich estimator for the heteroscedasticity variance estimation.

Meanwhile, in order to confirm the consistence and accuracy of the estimated results from *ESRM* above, we also report the results estimated from a two-stage instrumental variable (IV) approach below.

#### 4. Empirical model and variable description

The empirical equations to be estimated are the supply of adoption decision function and outcome functions. The adoption decision equation, which is equivalent to Equation (1), is specified as follows:



$$A_{iht} = \alpha_0 + \alpha_1 Z_{iht} + \alpha_2 C_{ct} + \alpha_3 I_{iht} + \alpha_4 V_{vt} + \alpha_5 H_{ht} + \alpha_6 F_{iht} + \alpha_7 P + \mu_{iht}. \quad (7)$$

The separate outcome equations for adopters and nonadopters, which is equivalent to Equations (2a) and (2b), are defined as follows:

$$Y_{1iht} = \beta_0 + \beta_1 A_{1iht} + \beta_2 C_{1ct} + \beta_3 I_{1iht} + \beta_4 V_{1vt} + \beta_5 H_{1ht} + \beta_6 F_{1iht} + \beta_7 P_1 + \varepsilon_{1iht} \\ \text{if } A_{iht} = 1, \quad (8a)$$

$$Y_{2iht} = \beta'_0 + \beta'_1 A_{2iht} + \beta'_2 C_{2ct} + \beta'_3 I_{2iht} + \beta'_4 V_{2vt} + \beta'_5 H_{2ht} + \beta'_6 F_{2iht} + \beta'_7 P_2 + \varepsilon_{2iht} \\ \text{if } A_{iht} = 0, \quad (8b)$$

where the subscripts of  $i$  and  $h$  represent the  $i^{\text{th}}$  farmland plot that farm HHs has and the  $h^{\text{th}}$  HH. The subscripts of  $v$  and  $c$  represent the village and county, respectively.  $t$  represents the year.  $\alpha$  and  $\beta$  are the vectors of parameters to be estimated.  $\mu_{iht}$  and  $\varepsilon_{iht}$  are the error terms, which is the same as in Equations (1) and (2). Appendix I presents the definition and descriptive statistics of variables used in the Equations (7) and (8).

$A_{iht}$  is the dependent variable in the adoption decision function, which indicates whether or not farm HHs adopt engineering measures for different farmland plots, taking the value 1 if the HH adopt measures and 0 otherwise. Appendix I shows that 37 per cent of farm HHs applied engineering adaptive measures in 2010–2012 (row 1).

$Y_{iht}$  is the dependent variable in the outcome functions, which indicates the crop yield or crop net income. Appendix I shows that HH average crop yield and crop net income are 11869.68 kg/ha and 14374.42 yuan/ha, respectively (rows 2 and 3).

$Z_{iht}$  is the IV for  $A_{iht}$  in the Equation (7), where there are two types of instrument variables used in the selection function. The first is access to the Government warning and prevention information against disaster. The second is access to the Government's technical, material or financial policy support against disaster. The estimated results from previous studies reveal that the public climate information and policy supports significantly facilitated farmers' adaptation decision-making with regard to climate change. Appendix I shows that 10 per cent and 31 per cent farm HH have accessed climate information and the technical, material or financial policy support against disaster in 2010–2012, respectively (rows 4 and 5).

The independent variables used in the two models are defined as follows:

Firstly, the climate change variables  $C_{ct}$  in this study include: (i) long-term climate change variables  $LCM_T$  and  $LCM_P$ , indicating that the mean of temperature and precipitation over the past three decades (1983–2012); and (ii) extreme weather event variables ( $D_D$ ) if it was the severe drought year and  $D_F$  if it was the severe flood year, indicating that the county experienced either severe drought or flood year over 2010–2012.

Secondly,  $I_{iht}$  is a set of production input variables, covering the costs of fertiliser, pesticide, machinery and total labour (including family labour and hired labour) at the plot level. Appendix I shows that the average inputs of fertiliser, pesticide and machinery are 4,935.89, 919.51 and 2,742.42 yuan, respectively, and the average labour input is 100.86 adult days per hectare (rows 10–13).

Thirdly, village characteristics ( $V_{vt}$ ) indicate the irrigation conditions in the village, which include if there is any irrigation and drainage infrastructure in the village  $V_{vt1}$  (1 = yes; 0 otherwise). Appendix I shows that 95 per cent of sample villages have infrastructure for irrigation or drainage.

Fourthly, HH characteristics ( $H_{ht}$ ) include variables as follows: (i) the assets that HHs possess ( $H_{ht1}$ ) are measured as the value of the durable goods, and the sample HHs have the value with an average of 10,380 yuan for durable goods; (ii)  $H_{ht2}$  indicates the proportion of farm income in total income for farm HHs, and the average proportion accounts for 47.5 per cent; (iii)  $H_{ht3}$  indicates if any members of the HHs received productive or technical training during the past 3 years (1 = yes; 0 otherwise), and Appendix I shows that 31 per cent of sample HHs received training in 2010–2012; (iv)  $H_{ht4}$  indicates the gender of the farms HH head (1 = male; 0 otherwise), where there are 96 per cent HHs whose head are men, only 4 per cent are women; (v) the explanatory variable  $H_{ht5}$  represents the education of the HH head, where the average education is 6.91 years; and (vi) the variable of farming experience of the HH head ( $H_{ht6}$ ) is used to test whether the experienced farmers are likely to adopt engineering measures and whether the farming experience has an impact on crop production. The average farming experience of the HH head is 35.27 years.

Fifthly, the characteristics of the farmland ( $F_{iht}$ ) are assumed to be important for adaptation decision and crop income function: (i) farmland area ( $F_{iht1}$ ), as is shown in Appendix I, is small with an average plot area of 0.2 ha; (ii) the types of farmland ( $F_{iht2}$ ) indicate that the plots are either plain or not, where Appendix I shows that there are 92 per cent farmland plots are flat, and 8 per cent other types; (iii) farmland tenure,  $F_{iht3}$ , indicates whether farmland has been leased/rented or not from other HH, where there is only 8 per cent farmland that have been transferred; and (iv) soil types of plots  $F_{iht41}$  indicate it is either sand or not;  $F_{iht42}$  indicates whether it is either loam or not;  $F_{iht43}$  indicates whether it is either clay or not.

Finally, we use province dummies (fixed effects at the provincial level) to control for the effects of province specific factors that do not change over time. And there are five provinces: Henan ( $P_1$ ), Hebei ( $P_2$ ), Shandong ( $P_3$ ), Jiangsu ( $P_4$ ) and Anhui ( $P_5$ ).

## 5. Results and analyses

### 5.1 The validity of instrument variables

We first test the validity of instrument variables. A valid selection instrument variable will significantly affect the adaptation decision rather than directly affect the crop yield (Table 4). According to Di Falco *et al.* (2011) and Huang *et al.* (2015), there will be a falsification test if the IVs impact the adaptation decision, but it will not affect the crop yield among nonadopters. Hence, if the total sample of adopters and nonadopters is used we cannot prove whether the change of crop yield is caused by the change of IVs or adaptation measures. The *t*-values of IVs are 5.56 and 10.19, respectively, in Model 1, showing that the access to the Government climate information and the access to the Governmental supports have jointly positive effects on farmer adaptation to climate change. The *t*-values are  $-0.85$  and  $0.39$ , respectively, in Model 2, suggesting that the IVs have not significantly affected crop yield. Therefore, we ensure the validity of the chosen IV.

### 5.2 The determinants of adaptation decision

The estimated results of the adaptation decision as to whether farm HHs took engineering measures are presented in column 2 of Table 5 and Table 6 with *ESRM*, which shows what the driving forces are for farm HHs to undertake engineering adaptive measures against climate change.

#### 5.2.1 Instrument variables

It can be seen the IV of access to the Government's technical, material or financial policy support against disaster has a significant and positive effect (0.115) on farm HH adaptation (row 22, Table 5) and the IV of access to the government warning and prevention information against disaster has significant and positive effect (0.331) on farm HH adaptation (row 21,

**Table 4** Parameter estimate tests on the validity of the selection instruments

Instrument variables (IV)	Model 1 $Y_1 = \text{adaptation (1/0)}$		Model 2 $Y_2 = \text{crop yield that HH did not adapt}$	
	Coefficient	<i>t</i> -Value	Coefficient	<i>t</i> -Value
Access to govt climate info against disaster ( $Z_{ht1}$ )	0.338***	5.56	$-171.915$	$-0.85$
Access to govt physical support against disaster ( $Z_{ht2}$ )	0.392***	10.19	67.188	0.39
Constant	$-0.493***$	$-21.73$	$11,609.57***$	118.20
$\chi^2$ (2)	$135.16***$	—	0.86	—
Observations (plot)	5,138	—	3,243	—

Table 6). This suggests that farm HHs be more likely to take engineering adaptation measures if they are able to access the climate information and the various physical supports against disaster. The reason may be that access to disaster warning and prevention information could strengthen farm HH awareness before any disaster and reduce the damage to a minimum during or after the disaster, such that the access to various physical supports could mitigate farm HH economic pressure and improve the possibility of adapting to climate change.

### 5.2.2 Climate change

Severe drought weather results in farm HHs being more likely to make adaptation decisions. Farmers who experienced a severe drought were 8.9 per cent more likely to undertake engineering adaptation measures against

**Table 5** The estimated results of farmers' adaptation decision and its impact on *crop yield* with endogenous switching regression

Variables	Adaptation decision	Crop yield (log)	
		Adopters	Nonadopters
(1)	(2)	(3)	(4)
$\log(\text{LCM}_T)$	-0.053 (0.231)	0.238** (0.106)	-0.237*** (0.08)
$\log(\text{LCM}_P)$	0.366 (0.407)	0.037 (0.167)	-0.68*** (0.229)
$D_D$	0.089* (0.049)	-0.048** (0.022)	-0.056** (0.024)
$D_F$	0.063 (0.055)	0.044** (0.021)	-0.091* (0.048)
$\log(I_{iht1})$	-0.092 (0.102)	0.811*** (0.055)	0.846*** (0.087)
$\log(I_{iht2})$	0.086* (0.049)	0.138*** (0.035)	0.022 (0.03)
$\log(I_{iht3})$	0.112 (0.084)	0.032 (0.032)	0.066** (0.028)
$\log(I_{iht4})$	-0.036 (0.105)	0.034 (0.023)	0.12 (0.062)
$V_{vt}$	-0.396* (0.246)	0.148 (0.092)	-0.237** (0.11)
$H_{ht1}$	0.004** (0.002)	-0.0002 (0.001)	-0.0002 (0.001)
$H_{ht2}$	-0.002 (0.001)	0.0001 (0.001)	0.001 (0.001)
$H_{ht3}$	0.164* (0.088)	-0.028 (0.037)	-0.022 (0.057)
$H_{ht4}$	-0.181 (0.169)	0.1 (0.104)	0.066 (0.1)
$H_{ht5}$	0.017 (0.013)	0.006 (0.005)	-0.004 (0.007)
$H_{ht6}$	0.006* (0.003)	-0.002 (0.002)	0.001 (0.002)
$F_{iht1}$	-0.15 (0.158)	0.016 (0.104)	0.299*** (0.116)
$F_{iht2}$	0.398* (0.237)	0.017 (0.167)	-0.2** (0.087)
$F_{iht3}$	0.131 (0.127)	0.061 (0.054)	0.053 (0.076)
$F_{iht42}$	0.081 (0.106)	0.004 (0.044)	-0.023 (0.056)
$F_{iht43}$	0.007 (0.097)	-0.013 (0.038)	0.014 (0.057)
$Z_{ht1}$	0.183 (0.2)	—	—
$Z_{ht2}$	0.115* (0.07)	—	—
Province dummies	YES	YES	YES
Constant	-3.739 (2.463)	1.411** (1.262)	5.03*** (1.511)
$\sigma_i$		0.372*** (0.059)	0.628*** (0.127)
$\rho_j$		0.1 (0.548)	-0.814** (0.319)
Obs. (plots)	5,138	1,895	3,243

Notes: \*, \*\* and \*\*\* represent significance 10%, 5% and 1% level, respectively. Both regressions are weighted by the ratio of village population to county population. Robust standard errors clustered at the household level are appeared in parentheses.

climate change (Table 5, row 3). In contrast, the mean of long-term temperature and precipitation has no significant impact on adaptation decision (Table 5, rows 1 and 2). This result is consistent with Bryan *et al.* (2009) who found that farmers' behaviour depends more on short-term climate variations and extreme weather events than long-term changes in the average and variability of rainfall and temperature over the period 1951–2000.

### 5.2.3 Input factors

The results show that pesticide input has significantly positive effect on the adaptation of farm HHs. This means that the more pesticide input used, the more likely farm HHs take engineering adaptive measures against climate change (row 6, Table 5). In particular, if pesticide input increases

**Table 6** The estimates of farmers' adaptation decision and its impact on *crop net income* with endogenous switching regression

Variables	Adaptation decision	Crop net income (log)	
		Adopters	Nonadopters
(1)	(2)	(3)	(4)
$\log(\text{LCM}_T)$	0.036 (0.225)	0.181*** (0.052)	0.266*** (0.032)
$\log(\text{LCM}_P)$	0.231 (0.444)	0.02 (0.088)	-0.136* (0.075)
$D_D$	0.104* (0.063)	-0.075*** (0.028)	-0.075*** (0.017)
$D_F$	0.076 (0.055)	0.018 (0.018)	-0.01 (0.018)
$\log(I_{iht1})$	-0.057 (0.061)	0.017 (0.016)	0.015 (0.009)
$\log(I_{iht2})$	0.089** (0.043)	0.052*** (0.019)	-0.013 (0.01)
$\log(I_{iht3})$	0.044 (0.062)	0.002 (0.01)	-0.001 (0.007)
$\log(I_{iht4})$	0.062 (0.058)	-0.017 (0.019)	-0.002 (0.01)
$V_{vt}$	-0.443 (0.336)	0.088 (0.069)	-0.059* (0.035)
$H_{ht1}$	0.004** (0.002)	-0.0002 (0.001)	0.0005 (0.0004)
$H_{ht2}$	-0.001 (0.001)	0.0002 (0.0003)	0.0003 (0.0002)
$H_{ht3}$	0.183* (0.099)	0.014 (0.043)	0.023 (0.021)
$H_{ht4}$	-0.158 (0.183)	0.054 (0.058)	-0.039 (0.037)
$H_{ht5}$	0.021 (0.016)	0.005 (0.005)	0.001 (0.004)
$H_{ht6}$	0.006 (0.004)	0.0001 (0.001)	0.001 (0.001)
$F_{iht1}$	-0.061 (0.22)	0.147*** (0.051)	0.094*** (0.025)
$F_{iht2}$	0.157 (0.253)	0.037 (0.075)	0.016 (0.027)
$F_{iht3}$	0.161 (0.131)	-0.02 (0.035)	0.043* (0.023)
$F_{iht42}$	0.058 (0.114)	0.033 (0.03)	0.05** (0.02)
$F_{iht43}$	0.005 (0.102)	0.024 (0.022)	0.038** (0.018)
$Z_{ht1}$	0.331** (0.149)	—	—
$Z_{ht2}$	0.066 (0.197)	—	—
Province dummies	YES	YES	YES
Constant	-3.32 (2.686)	2.234** (1.118)	3.746*** (0.465)
$\sigma_i$		0.189 (0.119)	0.206** (0.086)
$\rho_j$		0.415 (1.665)	-0.252 (0.783)
Obs. (plots)	5,138	1,895	3,243

Notes: \*, \*\* and \*\*\* represent significance 10%, 5% and 1% level, respectively. Both regressions are weighted by the ratio of village population to county population. Robust standard errors clustered at the household level are appeared in parentheses.

by 10 per cent, the possibility that farm HHs take irrigation and drainage engineering measures against climate change would increase by 0.86 per cent.

#### 5.2.4 Village irrigation condition

The condition of the village irrigation and drainage infrastructures is found to be a negative determinant of whether farm HHs undertake irrigation and drainage engineering measures against climate change. In other words, HHs would not be willing to invest whether it has relatively perfect engineering measures in village, for that the better infrastructures in village, the less possibility HHs suffer climate change.

#### 5.2.5 The HH characteristics

As expected, the production and technique training program and farming experience have positive and significant effects on the adaptation behaviour of irrigation and drainage engineering measures. In particular, the adaptation probability would significantly increase by 16.4 per cent (Table 5, row 12) if the farm HHs had previously undertaken a production and technique training program. Similarly, if the head of HH has one more year of farming experience, the adaptation probability would significantly increase by 0.6 per cent (Table 5, row 15). These findings are consistent with several previous studies (Gbetibouo *et al.* 2010; Teklewold *et al.* 2013; Asfaw *et al.* 2016). The quantity of HH assets has a significant and positive effect ( $H_{ht1} = 0.004$ ), on the HH decision as to whether to undertake irrigation and drainage engineering measures against climate change. Perhaps not surprisingly, the wealthier HHs are more likely to take irrigation and drainage engineering measures to offset climate risk than poorer HHs. This means that the poorer HHs are more vulnerable when they are faced with the climate change. This finding is consistent with many previous studies (Bryan *et al.* 2009; Comoé and Siegrist 2015).

#### 5.2.6 Farmland characteristics

Both the quantity and quality of the farmland have significant impacts on the HH adaptation to climate change. For example, the farmland type has a positive impact on HH adaptation decision-making (0.398, row 17, Table 5), showing that the greater the probability that farmers undertake irrigation and drainage engineering measures if the farmland is flat.

We found that the public services (both information and physical), the HH assets, village irrigation and drainage condition, and farmer training programs all significantly affect the adaptation behaviour of farm HH to under take irrigation and drainage engineering measures in response to climate change. Therefore, we conclude that in order to encourage farm HH to invest in irrigation and drainage engineering measures, Government should provide more public services, increase farmers' income, invest in rural irrigation infrastructure and enhance rural education and training programs.



### 5.3 The determinants of crop yield

The estimated results for the crop yield function are presented in columns 3 and 4 of Table 5, which helps to identify the determinants of crop yield for both adopter and nonadopter.

First, the sign of the correlation coefficients  $\rho_{1\mu}$  and  $\rho_{2\mu}$  have economic interpretations. The estimated  $\rho_{1\mu}$  and  $\rho_{2\mu}$  have alternate signs, which means that farm HHs undertake engineering adaptation based on their comparative advantage (Fuglie and Bosch 1995; Alene and Manyong 2007). Hence, those who adapt have above-average crop yield from adaptation and those who do not adapt have above-average crop yield from nonadaptation.

Second, most of the estimated coefficients in the crop yield function are statistically significant. The apparent differences in the estimated coefficients of factors clearly reveal the different effects of adapting engineering measures on crop yield between adopters and nonadopters (columns 3 and 4).

#### 5.3.1 Climate change

It is expected that engineering adaptations could mitigate the loss of crop yield under long-term climate change and extreme weather events. For example, the variables of mean of temperature and precipitation are found to have significantly negative impacts ( $-0.237$  and  $-0.68$ ) on the crop yield for nonadopters, but mean of temperature has positive impacts on the crop yield for adopters ( $0.238$ ). This suggests that the engineering adaptation reduces losses in crop yield or even increase crop yield under the long-term climate change. Furthermore, the variable for severe drought has a significantly negative effect ( $-0.056$ ) on crop yield for nonadopters and it has negative impact ( $-0.048$ ) on crop yield for adopters, which means that adopters suffer 0.8 per cent less crop yield loss than nonadopters. The variable for severe flood has a significantly negative effect ( $-0.091$ ) on crop yield for nonadopters, but it has positive impact ( $0.044$ ) on crop yield for adopters. This suggests that the engineering adaptation does reduce yield losses when floods occur.

#### 5.3.2 Input factors

Fertiliser, pesticide and machinery have a significant impact on crop yield but their coefficients are all less than unitary in terms of absolute value (rows 5–8), indicating all factor inputs are inelastic. However, given the fixed grain price, these results are consistent with previous findings on intensive and excessive use of factor inputs in China's grain production (Huang *et al.* 2008; Holst *et al.* 2013). In fact, Chen *et al.* (2013) found that there were apparent radical adjustment and slack adjustment of factor inputs for China's major wheat-producing provinces using an input-oriented DEA approach.

### 5.3.3 Farmland characteristics

The farmland characteristics also play a role in increasing crop yield. As expected, increasing arable land area can significantly increase crop yield for nonadopters (row 16, column 4).

From above discussion, we found that the engineering adaptation could mitigate the loss of crop yield from climate change; and increasing factor inputs has a little effect on crop yield due to current higher input level. However, return to scale can apparently increase HH crop yield.

## 5.4 The determinants of crop net income

Table 6 displays the estimated results based on the crop net income function. Observing and comparing the coefficients between Tables 5 and 6, we found that there are apparent differences in both magnitude and signs between Tables 5 and 6. This is particularly true for fertiliser. The estimated coefficient of fertiliser suggests that fertiliser has a significant effect on crop yield (Table 5, row 5), but it does not have any effect on crop net income (Table 6, row 5). Some factor inputs appear to have a negative effect on crop net income.

## 5.5 Effects of adaptation on crop yield and crop net income

Table 7 presents the estimates for the expected outcome and average treatments effects, which show the impact of engineering measures on crop yield and crop net income. The expected crop yield per hectare (log) and crop net income per hectare (log) in the actual case are presented in cells (a) and (b); the expected crop yield and crop net income in the counterfactual case are presented in cells (c) and (d). The average treatment effect estimates (ATT and ATU) (column 4) and change rate (column 5) account for selection bias arising from the fact that adopters and nonadopters may be systematically different (Huang *et al.* 2015).

The result for ATT suggests that the engineering adaptation significantly *increases* crop yield. Specifically, compared with the counterfactual case of that if HHs had not adapted, HHs who adapted would increase crop production by 9.26 per cent (row 1, column 5).

However, the result for ATU reveals that the engineering adaptation significantly *decreases* crop net income. Specifically, farmers who did not adapt would suffer decreases of 3.58 per cent in crop net income if they adapt (row 4, column 5).

The estimated results with a two-stage IV approach also suggest that the adaptation of engineering measures could increase crop yield, but reduce crop net income (Appendix II). Although the coefficients of  $A_{iht}$  are insignificant, the signs are opposite in the yield and income functions.

Previous studies pertaining to China focused on crop yield or output rather than profit margin. To better understand any differences from previous studies, we need to link China's grain production and its grain market.

**Table 7** Impact of engineering measures on crop yield and crop net income

Subsamples	Decision stage		Treatment effects	Change rate (%)
	To adapt	Not to adapt		
Average expected crop yield (log)				
Plots that adapted	(a) 9.305	(c) 8.516	ATT = 0.789***	9.26
Plots that did not adapt	(d) 9.183	(b) 9.228	ATU = −0.045	−0.49
Average expected crop net income (log)				
Plots that adapted	(a) 3.543	(c) 3.448	ATT = 0.095***	2.76
Plots that did not adapt	(d) 3.363	(b) 3.488	ATU = −0.125***	−3.58

Notes: \*\*\* denote significance at the 1% level. ATT represents the effect of the treatment (i.e. adaptation) on the treated (i.e. farmers that adapted), while ATU represents the effect of the treatment (i.e. adaptation) on the untreated (i.e. farmers that did not adapt).

Firstly, irrigation and drainage facilitates improvements in crop production, where historically the Chinese Government has paid particular attention to enhancing irrigation infrastructure. It has encouraged farmers to invest in irrigation and drainage engineering measures, especially when faced with extreme weather events and long-term climate change (NDRC 2013). Given improvements to the structure and scale of irrigation, farmers have been willing to use more inputs (e.g. fertiliser), with the expectation it will increase crop yield.

However, past experience has shown that the high costs of inputs or the low return from increased production has led to decisions and practices that are economically suboptimal. Attempts to increase national grain security seem to have come at the expense of farmers' net income (Godfray *et al.* 2010). For example, of the 20 corn-producing provinces, nine show a negative profit margin, ranging from -100 to -400 yuan per mu in 2014 (NAPCRD 2015). In 2015, almost all of the 20 corn-producing provinces (except for Inner Mongolia) experienced negative profit margins, ranging from -200 to -600 yuan per mu (NAPCRD 2016).

Ironically, this is particularly true for 'good' years. Whenever there is a good grain harvest, farmers face difficulty in selling their grain, which they can only do by reducing price, which depends on production and consumption and the inelasticity of grain demand. The unexpected surplus results from a positive yield shock, which is usually associated with a low market price when there is a good grain harvest (Yin *et al.* 2009; Gilbert and Morgan 2010; Zhou *et al.* 2012).

Given these types of situation, China's grain market has created a dilemma for policymakers: more output; more imports; and more storage, which are called 'Three Highs'. Hence, the Chinese Government began to implement supply-side reforms, aimed at reducing chemical inputs and sown area, to reduce planting intensity and protect arable land and the environment.

Chinese policymakers need to rethink some of their policies and incentives: (i) Is it necessarily a good idea for Chinese farmers to invest in irrigation and drainage engineering measures against extreme climate changes if net returns decline? (ii) What is the role of the Chinese government with regard to irrigation infrastructure? and (iii) What role do Chinese policymakers have in promoting capacity building in grain production?

## 6. Conclusion and implications

Long-term climate change alters the grain production environment, and frequent extreme weather events threaten food security and farmers' crop income, and therefore, adaptation to climate change has attracted a great deal of attention both domestically and globally. Using a large panel field survey data set across five major grain-producing provinces in China, this research has employed an endogenous switching regression to analyse the driving forces behind engineering adaptation measures and its impact on crop income of farm HHs.

The survey results show that nearly 40 per cent of HHs undertook some form of irrigation and drainage engineering measures to adapt to climate change. The extent of these measures was closely correlated with crop input levels and varies across HHs with differences in the characteristics of both farmers and their farms.

It is important to find that access to governmental services for drought and flood, and agricultural production training programs can help farmers to adapt to extreme weather events by taking irrigation and drainage engineering measures. However, in this study, only 10 per cent of farmers can access the governmental climate information services, 31 per cent of farmers can access governmental technical, physical and financial supports, and 31 per cent of farmers attended production and technical training program. Clearly, there is room to incorporate climate change adaptation services into China's public extension system.

This study also found that positive adaptation decisions significantly mitigated the loss of crop yield and even increase crop yield under long-term climate change and extreme weather events, but most of value of crop yield was offset by rising factor input costs. Specifically, compared with the counterfactual case of that if HHs had not adapted, HHs who adapted would increase crop production by 9.26 per cent. However, for farmers who did not adapt, they would decrease 3.58 per cent of crop net income. This indicates that rising crop yield could not proportionally increase farmers' net income.

These findings indicate that it is contradictory for China to encourage farmers to take adaptive measures and increase crop production inputs. How these two goals are reconciled is a crucial problem for China to solve if there is to be future sustainable crop production and national poverty reduction. Therefore, this issue should be considered with the implementation of current

national agricultural supply-side reform, such as reducing the multiple crop index and pesticide and fertiliser inputs, and increases in the use of organic manure input to protect the soil environment and recover organic matter content.

The adaptive capability building for the poor HHs in response to extreme events is another priority of policy intervention. The positive influence of household assets on taking irrigation and drainage engineering measures suggests that the poor, who normally lack sufficient capital, are more vulnerable in the face of extreme weather events. Therefore, governmental supports, such as technical or physical supports, are particularly important for the poor to enhance their adaptation ability against climate changes.

Finally, as farmers have been suffering increasingly frequent and severe extreme weather events in many developing countries, we believe our findings also have some implications for other similar large developing countries in terms of their national climate adaptation and farmers' income promoting plans.

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**Appendix 1** The definition and description of variables used in the models

Variables	Definition	Mean	SD
<b>Dependent variables</b>			
Adaptation ( $A_{iht}$ )	1 = adopter; 0 otherwise	0.37	0.48
Crop yield ( $Y_{iht}$ )	kg/ha	11869.68	3649.65
Crop net income ( $Y_{iht}$ )	Yield $\times$ price-total cost ( $10^3$ yuan/ha)	14.37	7.31
<b>Instrument variables</b>			
Access to govt climate info against disaster ( $Z_{ht1}$ )	1 = yes; 0 otherwise	0.10	0.29
Access to govt tech., material or financial supports against disaster ( $Z_{ht2}$ )	1 = yes; 0 otherwise	0.31	0.46
<b>Independent variables</b>			
Exposure to climate change ( $C_{ct}$ )	—	—	—
Long-term climate change	—	—	—
Mean of temperature (LCM <sub>T</sub> )	1983–2012 (°C)	13.46	3.10
Mean of precipitation (LCM <sub>P</sub> )	1983–2012 (mm)	721.05	179.44
Extreme weather events	—	—	—
If severe drought year ( $D_D$ )	1 = yes; 0 otherwise	0.37	0.48
If severe flood year ( $D_F$ )	1 = yes; 0 otherwise	0.13	0.34
Inputs ( $I_{iht}$ )	—	—	—
Fertiliser ( $I_{iht1}$ )	The cost(yuan/ha)	4,935.89	2,112.63
Pesticide ( $I_{iht2}$ )	The cost (yuan/ha)	919.51	775.58
Machine ( $I_{iht3}$ )	Total cost (yuan/ha)	2,742.42	1,310.18
Labour ( $I_{iht4}$ )	Adult days/ha	100.86	94.69
Village characteristics ( $V_{vt}$ )	—	—	—
If irrigation/drainage infrastructures ( $V_{vt1}$ )	1 = yes; 0 otherwise	0.95	0.22
HH characteristics ( $H_{ht}$ )	—	—	—
Asset of HH ( $H_{ht1}$ )	The durable goods ( $10^3$ yuan)	10.38	19.57
Agricultural income ( $H_{ht2}$ )	% of agri. income in total	47.50	33.73
Production/technical training ( $H_{ht3}$ )	If attending training (1 = yes; 0 otherwise)	0.31	0.46
Gender of HH head ( $H_{ht4}$ )	1 = male; 0 otherwise	0.96	0.20
Education of HH head ( $H_{ht5}$ )	Year attended	6.91	3.17
Farming experience of HH head ( $H_{ht6}$ )	Year	35.27	11.37
Farmland characteristics ( $F_{iht}$ )	—	—	—
Farmland area ( $F_{iht1}$ )	Hectare	0.20	0.17
Farmland types ( $F_{iht2}$ )	1 = plain; 0 otherwise	0.92	0.27
If farmland is transferred ( $F_{iht3}$ )	1 = yes; 0 otherwise	0.08	0.28

**Appendix 1** (Continued)

Variables	Definition	Mean	SD
If sand or not ( $F_{iht41}$ )	1 = yes; 0 otherwise	0.28	0.45
If loam or not ( $F_{iht42}$ )	1 = yes; 0 otherwise	0.33	0.47
If clay or not ( $F_{iht43}$ )	1 = yes; 0 otherwise	0.39	0.49
Province dummy ( $P$ )	—	—	—
Henan ( $P_0$ )	1 = yes; 0 otherwise	0.20	0.40
Hebei ( $P_1$ )	1 = yes; 0 otherwise	0.19	0.40
Shandong ( $P_2$ )	1 = yes; 0 otherwise	0.20	0.40
Jiangsu ( $P_3$ )	1 = yes; 0 otherwise	0.21	0.41
Anhui ( $P_4$ )	1 = yes; 0 otherwise	0.20	0.40

**Appendix 2** The estimated results on adaptation decision, crop yield and crop net income

Variables	Adaptation decision	Crop yield (log)	Crop net income (log)
$A_{iht}$	—	0.211 (0.286)	−0.109 (0.119)
$Z_{ht1}$	0.333** (0.147)	—	—
$Z_{ht2}$	0.084 (0.089)	—	—
$\log(\text{LCM}_T)$	0.033 (0.292)	0.14** (0.069)	0.22*** (0.027)
$\log(\text{LCM}_P)$	0.227 (0.586)	−0.454*** (0.145)	−0.067 (0.06)
$D_D$	0.118** (0.056)	−0.031** (0.014)	−0.07*** (0.007)
$D_F$	0.077 (0.068)	−0.006 (0.025)	0.011 (0.01)
$\log(I_{iht1})$	−0.053 (0.059)	0.839*** (0.07)	0.016** (0.008)
$\log(I_{iht2})$	0.083* (0.045)	0.052** (0.025)	0.004 (0.006)
$\log(I_{iht3})$	0.033 (0.043)	0.059*** (0.022)	0.003 (0.006)
$\log(I_{iht4})$	0.062 (0.062)	0.117*** (0.045)	−0.004 (0.008)
$V_{vt}$	−0.386 (0.42)	−0.111 (0.083)	−0.008 (0.028)
$H_{ht1}$	0.004** (0.002)	0.0003 (0.0005)	0.0002 (0.0003)
$H_{ht2}$	−0.001 (0.001)	0.0009* (0.0004)	0.0003 (0.0002)
$H_{ht3}$	0.174* (0.102)	−0.022 (0.038)	0.025* (0.015)
$H_{ht4}$	−0.168 (0.191)	0.056 (0.069)	−0.02 (0.028)
$H_{ht5}$	0.023 (0.017)	0.003 (0.005)	0.004* (0.002)
$H_{ht6}$	0.005 (0.004)	0.001 (0.001)	0.001 (0.001)
$F_{iht1}$	−0.065 (0.229)	0.21** (0.095)	0.098*** (0.032)
$F_{iht2}$	0.126 (0.179)	−0.159* (0.085)	0.02 (0.026)
$F_{iht3}$	0.155 (0.126)	0.063 (0.047)	0.019 (0.019)
$F_{iht42}$	0.065 (0.121)	−0.017 (0.037)	0.043*** (0.016)
$F_{iht43}$	0.006 (0.119)	0.00001 (0.037)	0.034** (0.014)
Province dummies	Yes	Yes	Yes
Constant	−3.245 (3.477)	3.673*** (0.967)	3.673*** (0.967)

Notes: \*, \*\* and \*\*\* represent significance 10%, 5% and 1% level, respectively. Both regressions are weighted by the ratio of village population to county population. Robust standard errors clustered at the household level are appeared in parentheses. The sample is 5,138 ( $2,569 \times 2$  years).