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Farmers' perceptions of drought-severity and the impacts on *ex-ante* and *ex-post* adaptations to droughts: Evidence from maize farmers in China

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ABSTRACT

This study examines the impacts of farmers' drought-severity perceptions on two adaptation strategies—*ex-ante* use of drought-tolerant varieties and *ex-post* irrigation use—employing a large-scale survey data of maize farmers in northern China. The former is helpful for saving water while the latter may increase the intensity of water use in drought season. An endogenous switching probit model is employed to account for the potential selection bias and endogeneity of farmers' drought-severity perceptions in regressions of adaptation strategies. The results show that perceiving increasing drought-severity might increase farmers' probabilities of using drought-tolerant varieties (DTVs) by 8.1% on maize plots but lower the probability of irrigation by 15.1%. However, once the use of the DTVs is controlled for, the perception of drought-severity has no additional predictive powers for irrigation. Furthermore, the use of drought-tolerant varieties may reduce the probability of irrigation by 27.5%. The findings highlight the need for policymakers to enhance farmers' perceptions and differentiate adaptation options and consider their interrelationships in allocating resources to maximise their effectiveness.

1. Introduction

Frequent and severe droughts with longer durations are the likely outcomes of increased climate variations for many countries (e.g. Leng et al., 2015; Calzadilla et al., 2013), which will negatively affect agricultural productivity and farm household livelihoods. Identifying adaptation strategies to prevent and/or mitigate the negative effects has important implications for rural welfare and is an issue that policymakers must address. Farmers' adaptations to drought risk are also key for food security, competitiveness of rural communities, environmental pollution, and resource depletion (Wang et al., 2021). The relatively large literature on adaptation strategies show that adaptations come in a wide variety of forms, such as crop choices, crop insurance, tillage, diversification, off-farm labour allocation, risk management strategies etc. (Smit and Pilifosova, 2001; Ding et al., 2009; Meraner and Finger, 2019; Turvey and Kong, 2010). These strategies can differ by purposefulness (autonomous vs planned), temporal scope (short- or long-term), spatial scope (individual, local, regional, national, or global), and form (technical, behavioural, financial, and institutional). One important way of differentiation is based on whether adaptations are implemented before (*ex-ante* adaptation) or after (*ex-post* adaptation) the occurrence of extreme weather events (Smit et al., 2000).

Distinguishing between *ex-ante* and *ex-post* adaptations can improve design of climate policies and allocations of funds. Rural households in developing countries are among the most vulnerable to adverse impacts of climate change (Barbier and Hochard, 2018). They usually do not have access to emergency funds, credit or community resources and can only cope with negative shocks *ex-post* (Báez et al., 2017). Implementing *ex-ante* adaptations can be more beneficial and cost-effective for such groups. Simulations by Owens et al. (2004) show that reallocating funds from *ex-post* responses to drought shocks to *ex-ante* actions could raise household welfare. The relationships between *ex-ante* and *ex-post* adaptations also provide important policy implications. For example, if *ex-ante* and *ex-post* adaptations are substitutes in terms of adaptive actions and *ex-ante* measures are more effective, additional resources should be allocated to *ex-ante* measures. However, only a few studies distinguish between *ex-ante* and *ex-post* adaptations (e.g. Hertel, Lobell, 2014).

Many studies also focus on identifying the factors that influence adaptation decisions (Deressa et al., 2009; Wolf et al., 2013; Chen et al.,

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2014; Huang et al., 2015; Wang et al., 2015; Alam et al., 2016; Hou et al., 2017; Dang et al., 2019; Islam et al., 2020). One such factor is the perception of increased climate variations including extreme weather events. Different studies have measured perceptions differently. The indicators constructed include perceptions of climate or drought trends and variability (e.g. Maddison, 2007; Rashid et al., 2014; Hou et al., 2017), concerns of climate change impact (e.g. Shi et al., 2015), judgements of causes of climate change (e.g. Yu et al., 2013), and perceived local vulnerability (Spence et al., 2011). Lee et al. (2015) found that the perception of local temperature change was the strongest predictor of climate change risk perceptions in many African and Asian countries. Among the few studies that focus on farmers' perceptions, measurements are more unified and often related to changes in temperature and/or precipitation. For example, Salau et al. (2012) reported that 63% of the Nigerian farmers perceived rising temperature and 70% perceived erratic rainfall. Rashid et al. (2014) reported that farmers in Bangladesh perceived overall changes in rainfall patterns, temperatures, and frequency and intensity of cyclonic storms.

Understanding climate change perceptions can be a critical step in enhancing adaptation capacity for several reasons. First, climate change perceptions can motivate the public to act to respond to climate change and to comply with policy measures (Shi et al., 2015; Yu et al., 2013). Spence et al. (2011) showed that respondents from the United Kingdom who perceived a greater local vulnerability to climate change impacts were more prepared to reduce their energy use. Hou et al. (2017) demonstrated that Chinese farmers who perceived increasing drought severity were more likely to adapt by using water-saving technologies. In India, by increasing the shared notion of risk and vulnerability, climate variability perceptions facilitated adaptive responses such as the formation of the Apple Growers' Association (Vedwan, 2006). Second, it is possible to influence stakeholder perceptions through measures such as information campaigns. Hou et al. (2017) found that providing early warnings of droughts to Chinese farmers increases the likelihood of a perception of increased drought-severity by 20%. Third, there is room for improving stakeholders' climate change perceptions. Hou et al. (2015) found that only 18% of the sample Chinese farmers had perceptions of local temperature change that were consistent with the actual trend calculated with climate data recorded at meteorological stations.

This study aims to analyze the linkages between farmers' climate change perceptions in terms of drought severity and *ex-ante* and *ex-post* adaptations. In theory, the impacts of farmers' drought-severity perceptions on their *ex-ante* and *ex-post* adaptations can be derived,[1] based on the expected utility model, by referring the studies of Foudi and Erdlenbruch (2012), Lehmann, N. and Finger (2014) and Jianjun et al. (2015). While previous studies have focused on the relations between farmers' perceptions and adaptation strategies (e.g. Spence et al., 2011; Fosu-Mensah et al., 2012; Comoé et al., 2014), few analyses empirically investigate the possible difference in the impacts of perceptions on *ex-ante* and *ex-post* adaptations and particularly explore the impact of using *ex-ante* adaptation strategies on the use of *ex-post* adaptation strategies. In practice, farmers have many adaptation strategies to drought risks, for instance, adopting new technology, planting new crop varieties, purchasing crop insurance, crop diversification, investing in irrigation infrastructure (Jianjun et al., 2015). This study focuses on the use of drought-tolerant varieties and irrigation, as they are the most direct related measures with water. The study on these two strategies helps better understand the design of agricultural water-saving strategies under drought risks. To achieve the objectives, a large-scale farm survey data in China were applied in this study. An endogenous switching probit model is used to solve the potential endogeneity of farmers' perceptions in their decision process.

The rest of the paper is organised as follows. Section 2 presents the data sources and the employed methods. Section 3 reports the descriptive statistics of farmers' drought-severity perceptions and their *ex-ante* and/or *ex-post* adaptations, and also reports the estimation results of empirical models. The final section concludes with major findings and policy implications.

2. Materials and methods

2.1. Data sources

The data used in this study are from a nationally representative survey conducted at the end of 2012, which covers nine provinces in China's five major grain-producing regions. The spatial distributions of water resources are not even in China. Although south China has relatively abundant water resources, north China is one of the most water-scarce areas worldwide and is vulnerable to droughts (Ji et al., 2010). Therefore, this study only includes sample provinces located in north China: five provinces in North China Plain (Hebei, Henan, Shandong, Anhui, and Jiangsu) and Jilin province in Northeast China. Overall, these six provinces produced over 40% of China's maize in 2015 according to China's national statistical data.

In each sample province, we first identified all the counties that experienced one or more drought years as well as normal years during the 2010–2012 period. China's national standard for natural disasters established by the China Meteorological Administration classifies the severity of drought into four categories: most severe (4), severe (3), moderate (2), and small (1). A drought year is defined as a year during which one or more level 3 or 4 droughts have occurred, while other years are categorised as normal years. Three counties were then randomly selected from all the counties that experienced both drought and normal years.

Within each county, townships were stratified into three groups based on the share of irrigable land areas and the degree of reliability of irrigation water supply, as assessed by the county's Water Conservancy Bureau. Random selection of one township, three villages in that township, and ten farm households from each village, was conducted, respectively. For each sample household, two plots were randomly selected from all the plots that were cultivated during both the drought and normal years. Plots that grew the same crop in both years were given higher priority of selection. Only sample households that grew maize were included. Each maize household may have one or two plots that were surveyed. The final sample included 1695 maize plots from 1058 households in 123 villages from 14 counties.

During the survey, household heads and village leaders were interviewed with separate questionnaires. Household heads were asked to report if they thought drought-severity (i.e. the number of days that drought lasted) over the past decade had increased, decreased, or shown no observable change. For each selected plot, we asked the respondents whether they used DTVs and how many times they irrigated maize. These questions were asked for both the normal and drought years. Table A.5 in Appendices A shows farmers' perception of drought-severity and the adoptions of DTVs and irrigation under the different perceptions. Obviously, when farmers perceive increasing drought severity, their adoptions of DTVs and irrigation are significantly different with others. Thus, farmers perception of drought can be further treated as dummy variable—perception of increasing drought severity (1 =yes, no=others). While there are 8 farmers reporting no observable change of drought severity, these samples only occupy less than 1% of total sample and will not lead to bias results due to assigning into other group. The survey also collected information on farmers' characteristics (e.g. age, education, gender, and family size), farm characteristics (e.g. farm size and distance to the nearest agriculture supply shop). Village leaders were interviewed for gaining information on village characteristics (e.g. proportion of irrigable land, and availability of drought-

[1] A detailed theoretical framework regarding the impacts of farmers' drought-severity perceptions on their *ex-ante* and *ex-post* adaptations can be found in Appendices B.

mitigation support in the village).

2.2. Methods

This section presents the methods to examine how farmers' drought-severity perceptions influence their adaptive actions. In our analysis, we can control for many factors that have been identified to influence farmers' perceptions of and their adaptation to climate change, such as demographic and socio-economic factors, geography, and access to extension service (Rashid et al., 2014; Hou et al., 2015; Lee et al., 2015; Leiserowitz, 2007; Akter and Bennett, 2011; Deressa et al., 2011; Dang et al., 2014). However, there might still be unobservable or missing factors due to a lack of information (Oster, 2019). For example, cognitive and psychological factors, such as fatalism, values, and cultural worldviews can shape perceptions of climate change and adaptive behaviours (Shi et al., 2015; Spence et al., 2011; Lorenzoni and Pidgeon, 2006; Wolf et al., 2013; Weber, 2010; Grothmann and Reusswig, 2006). Agricultural water related policies (e.g. pricing, quotas etc.) may also affect farmers' DTVs use and irrigation use (Lehmann and Finger, 2014), while the policy effect can be controlled by the township dummy variables as the implementation of related policies are supposed to be same in a township. Past exposure to extreme weather events is another such factor (Spence et al., 2011). Besides, in regressions on adaptive actions, perception may be endogenous and reverse causality may exist. Past use of adaptive strategies may modify farmers' perception because drought impacts may be altered by adaptation. It is essential to account for the potential perception endogeneity in case one or more important factors are excluded. Furthermore, the coefficients of explanatory variables, which measure their effects on adaptive actions, may vary among farmers that perceive increasing or lower drought-severity.

To address above issues, following previous studies (Lokshin and Glinskaya, 2008; Gregory, Colemanjensen, 2013; Ayuya et al., 2015), we employ the endogenous switching probit model (ESPM) based on the instrumental variable and full information maximum likelihood methods. The ESPM model takes into account unobserved variables that could simultaneously affect farmers' drought-severity perceptions and adaptive actions (Lokshin and Glinskaya, 2008). The instrumental variable approach could address the potential endogeneity issue for farmers' drought-severity perceptions in explaining their adaptive actions. The full information maximum likelihood method (FIML) is used to simultaneously estimate the equations of farmers' drought-severity perceptions and adaptive actions to obtain consistent standard errors of the estimates (Lokshin and Sajaia, 2011). Also, the ESPM has one advantage that is the possibility of deriving probabilities in counterfactual cases for the impacts of farmers' drought-severity perceptions on their adaptations by simulating the average treatment effect (Lokshin and Sajaia, 2011; Ayuya et al., 2015).

While there are also some other approaches such as propensity score matching (PSM) approach or inverse probability weighted regression adjusted (IPWRA) estimators which could be used to estimate the impact of farmers' drought-severity perceptions on their adaptations using observational data, these approaches can not control the selection bias led by unobservable factors (Oster, 2019) and hence are not superior to the ESPM in addressing the mentioned issues. Hence, in this section, the ESPM is used to estimate the perception effects on *ex-ante* and *ex-post* adaptations.

2.2.1. Impact of drought-severity perceptions on farmers' adaptations

A two-stage approach is used to model farmers' drought-severity perceptions and their influence on *ex-ante* and *ex-post* adaptations to drought. In the first stage, the latent variable P_i^*, measuring the drought-severity perception of farmer i, is expressed as a function of observable variables as:

$$P_i^* = \mathbf{z}'_i\alpha + \varepsilon_i,\ P_i = \mathbf{1}(P_i^* > 0) \tag{2.1}$$

where $\mathbf{1}(\bullet)$ is an indicator function and P_i is a binary variable that equals one if $P_i^* > 0$ and zero otherwise. We divide farmers into two groups based on their perceptions: ***perceivers of increasing drought*** ($P_i = 1$) are farmers who thought drought-severity had increased, and ***non-perceivers of increasing drought*** ($P_i = 0$) are farmers who thought it had decreased or shown no observable change over the past decade. Farmers who reported they had no judgement of the trend were also put into non-perceivers. The vector $\mathbf{z}_i$ contains variables that affect farmers' drought-severity perceptions and ε_i is the error term with a mean zero.

In the second stage, an endogenous switching framework is used to model the perception influence on adaptive actions wherein farmers face the two regimes defined in Eq. (2.1): perceivers ($P_i = 1$) and non-perceivers ($P_i = 0$).

$$V_{1im}^* = \mathbf{x}'_{1im}\theta_1 + u_{1i},\ V_{1im} = \mathbf{1}(V_{1im}^* > 0) \text{ if } P_i = 1 \tag{2.2a}$$

$$V_{0im}^* = \mathbf{x}'_{0im}\theta_0 + u_{0i},\ V_{0im} = \mathbf{1}(V_{0im}^* > 0) \text{ if } P_i = 0 \tag{2.2b}$$

where V_{im} is a binary variable that equals one if DTVs or irrigation is used on plot m of farmer i. The subscripts 1 and 0 represent perceivers and non-perceivers, respectively. Although the information on irrigation number is available, among all irrigated maize plots, more than 80% were only irrigated once or twice. Therefore, the irrigation number cannot be treated as a continuous variable. It is also difficult to run an endogenous switching model with ordinal dependent variables. Therefore, a dummy variable that indicates a plot is irrigated is used as the dependent variable to examine the impact of climate change perception on irrigation as an adaptive action.

The ESPM has been used in many previous studies that have binary selections and binary outcomes (Lokshin and Glinskaya, 2008; Gregory, Colemanjensen, 2013; Ayuya et al., 2015; Min et al., 2017). We follow the procedure developed by Lokshin and Sajaia (2011) and account for the potential endogeneity of drought-severity perceptions by estimating a simultaneous system of Eqs. (2.1), (2.2a), and (2.2b) using full information maximum likelihood estimation (FIML). The error terms in the above-mentioned equations are assumed to be jointly normally distributed with zero means. As V_{1im}^* and V_{0im}^* are never observed for the same farmer/plot, the covariance between u_{1i} and u_{0i} is not defined. However, the estimation can still be carried out using the bivariate normal distribution between u_{1i} and ε_i and between u_{0i} and ε_i, with their correlations defined as ρ_1 and ρ_0, respectively (Lokshin and Sajaia, 2011).

The estimation results of ESPM can be used to calculate the effects of increasing drought-severity perceptions on the use of adaptation strategies. Following Lokshin and Sajaia (2011), Ayuya et al. (2015), and Min et al. (2017), the effect of the treatment of "increasing drought-severity perception" on the treated (TT) is:

$$\mathrm{TT}(\mathbf{x}_{im}) = \Pr(V_{1im} = 1|\ P_i = 1, \mathbf{x}_{im}) - \Pr(V_{0im} = 1|\ P_i = 1, \mathbf{x}_{im}) \tag{2.3}$$

where $\Pr(V_{1im} = 1|\ P_i = 1, \mathbf{x}_{im})$ and $\Pr(V_{0im} = 1|\ P_i = 1, \mathbf{x}_{im})$ are the probabilities of using an adoption strategy on a plot by a farmer who perceives and one who does not perceive increasing drought-severity, respectively. It is constructed using the FIML estimation results. Eq. (2.3) measures the effect of increasing drought-severity perceptions on the likelihood of using adaptation strategies among perceivers. The average treatment effect on the treated (ATT) can be imputed by averaging Eq. (2.3) over the sample observations that perceived increasing drought-severity ($P_i = 1$):

$$\mathrm{ATT} = \Sigma\mathrm{TT}(\mathbf{x}_{im})^{\mathbf{1}(Pi\ =\ 1)}/N_{Pi\ =\ 1} \tag{2.4}$$

where $\mathbf{1}(P_i = 1)$ is the indicator function for perceivers and $N_{Pi\ =\ 1}$ is the number of observations with $P_i = 1$ (perceivers). Similarly, ATT can also be imputed for any subgroup of the sample by averaging Eq. (2.3) over all observations in that subgroup. The estimates of ATT for subgroups provide an opportunity to detect the heterogeneous treatment impacts among subgroups and thereby can derive somewhat policy implications.

Thus, usually, heterogeneity analysis is conducted by choosing an explanatory variable of policy relevance and estimating the treatment effects for subsamples defined by this variable. In the empirical analysis, we assess ATTs for subgroups defined by access to irrigation, weather conditions (drought or normal year), farm size, availability of drought-mitigation support, and distance from plot to the house.

The vector $\mathbf{x}_{im}$ contains variables that may influence either costs or benefits of adaptation strategies. Five groups of variables are used. The first measure plot characteristics such as plot size, soil type, and distance to a farmer's house, as well as whether a plot has access to irrigation. The size of a plot affects the extent of the exposure to weather risks in agricultural production. It can also affect the benefit or the cost of the adaptive action. Farmers with more fertile soil may be better buffered from the negative impacts of droughts. Therefore, they may be less likely to take adaptive actions. The second group measures farm characteristics such as age, gender, and education of the household head, family size, and share of family members that are engaged in off-farm work. All these variables affect farmers' adaptive decisions. For example, access to off-farm employment opportunities can reduce the impact of shocks to agricultural production on rural households, and thus, may affect their incentives to take adaptive actions (Giles, 2000). Income from off-farm jobs can be also used as an adaptation investment in the agricultural sector. The third group measures farm characteristics such as farm size and distance to the nearest agriculture supply shop. The fourth group includes two village-level variables. The first variable indicates the availability of drought-mitigation support in the village. Drought-mitigation support in rural China can include technical assistance to farmers to set up adaptive measures, post-disaster cash, or in-kind assistance. Extension services that provide technical support for drought-mitigation can be an important means for farmers to gain information on the likelihood of droughts as well as technical knowledge of mitigation strategies. Post-disaster assistance, however, may hamper farmers' incentive to be proactive. The share of irrigable land in the village reflects the overall irrigation conditions of the village. Current weather conditions such as levels of precipitation and temperature may affect the likelihood of using adaptation strategies. This is particularly relevant for *ex-ante* actions. The fifth group includes a year dummy that equals one for a drought year and township dummies. Data on weather variables are only available at the county level in China. The use of the township and year dummies in the regression helps control for current weather conditions to a large extent. In the empirical analysis that examines the use of irrigation as an adaptation strategy, only plots with access to irrigation are included. The variable that indicates a plot has access to irrigation is thus removed from $\mathbf{x}_{im}$. Table A.1 in Appendices A reports summary statistics of the explanatory variables used in this study, while Table A.2 in Appendices A compares the means of the explanatory variables contained in $\mathbf{x}_{im}$ between plots that used an adaptation strategy (DTVs or irrigation) and those that did not.

For the ESPM to be identified, the vector $\mathbf{z}_i$ should contain at least one variable that is not in $\mathbf{x}_{im}$ and can be used as the exclusion restriction. For each farmer i, we average the drought-severity perceptions of other farmers in the same village, AP_i. Such a cluster-effect instrument has been used in previous studies (Ji et al., 2010; Zhao et al., 2014). Farmers' perceptions of climate change are often influenced by peers. However, perceptions of peers are unlikely to directly influence a farmer's adaptation decisions except through their influence on the farmer's perception. Therefore, AP_i is a potential candidate for a selection instrument. It is noticed that in a same township, farmers normally share the agricultural extension services and supplier and output markets, accordingly they may also directly influence respective activities such as irrigation and seed choice. This means that the adaptation strategies of peers may also affect a farmer's adaptation decision. Nevertheless, this situation does not matter for the estimation using the perception of peers as an instrumental variable. Following previous studies (Di Falco et al., 2011; Ayuya et al., 2015; Huang et al., 2015; Parvathi and Waibel, 2016), falsification tests are performed. Results in Table A.3 of Appendices A support the validity of the AP_i variable as a selection instrument. The coefficient of the AP_i variable is statistically significant when perception is the dependent variable (column 1). In columns 2 and 3, where only non-perceivers are included ($P_i = 0$) and the dependent variables are the two adaptation strategies (the use of DTVs and irrigation), the coefficients of the AP_i variable are not statistically significant. Additionally, weak-instrument tests using F statistics reject the null hypothesis of a weak-instrument.

2.2.2. Relationship between the use of DTVs and irrigation

The analysis of the relationship between *ex-ante* and *ex-post* adaptations can yield useful policy advice. If DTVs and irrigation were substitutes in preventing/mitigating the negative impacts associated with droughts, policymakers could focus on just one instead of both strategies. For example, in areas with scarce water resources, the use of DTVs may be preferred due to the additional benefit of water conservation. For farmers without access to irrigation, planting DTVs also has the advantage of not requiring a high upfront fixed investment, unlike the development of new irrigation facilities.

The relationships between DTVs and irrigation can be assessed by examining if the decision to use one strategy is influenced by the use of another strategy. However, the use of one strategy is likely to be endogenous in the regression on the decision to use another strategy. This may be the case even when we examine the influence of an *ex-ante* strategy on an *ex-post* strategy. Although the use of DTVs precedes the irrigation decision temporally, it may still be an endogenous variable. This can happen due to the omission of factors such as past exposures to droughts that can influence both decisions. A valid instrumental variable (IV) would only affect farmers' decisions to use DTVs. The usage rate of DTVs among other farmers in the same village is employed to instrument for a farmer's DTV use. This is likely to be influenced by peers. Affected by peers' adoption of DTVs, a farmer may have a similar adoption decision to DTVs before seeding maize; hereafter, the farmer's DTVs adoption situation further influences the decision to irrigation during the growing season of maize. The results of falsification tests valid this proposed IV empirically too.

Two models are used, namely, a probit model (where the dependent variable is a dummy variable that indicates a plot is irrigated and DTV use is an explanatory variable) and the ESPM. In the first stage, a selection equation is run with DTV use as the dependent variable. In the second stage, an endogenous switching model is employed to model DTV use impact on irrigation decisions where farmers face two regimes: using or not using DTVs.

3. Results and discussion

3.1. Descriptive statistics

Although some studies predict the changes in drought-severity, duration, and frequency in China (e.g. Leng et al., 2015), there is no consensus on this among the sample farmers. Most farmers (71%) perceive increasing drought-severity (Table A.2 in Appendices A). Sample data also reveal a sharp difference in the use rates of the two adaptation strategies with DTVs being used on 26.8% of the plots. Irrigation is more widely used. About 76% of the plots have access to irrigation, of which, about 79% were irrigated during the survey years.

Table A.4 in Appendices A shows that the difference in shares of maize plots with DTVs in normal and drought years (26.8% and 26.4%, respectively) is not statistically significant. The same is the case when farmers are divided into perceivers and non-perceivers. These observations offer support for treating DTVs' use as an *ex-ante* adaptation strategy. The decision is typically made before farmers observe the actual weather conditions during the growing season, and thus, is less correlated with the occurrence of droughts. In contrast, DTV use seems to be positively correlated with perceptions of increasing drought-severity. In normal years, DTVs are used on 29.2% and 21.5% of plots

Table 1
Estimation results of drought-severity perception and the use of drought-tolerant varieties.

Variable	Endogenous switching probit model		
		Use of drought-tolerant varieties	
	Drought-severity perception	Drought-severity perception= 1	Drought-severity perception= 0
Drought-severity perception (1 =Yes;0 =Otherwise)			
IV for Perception[a]	2.318***		
	(0.162)		
Plot size (ha)	0.004	–0.545***	–0.697***
	(0.119)	(0.150)	(0.219)
Soil type (baseline=sandy)			
Loam (1 =Yes;0 =Otherwise)	–0.344***	–0.213**	–0.123
	(0.081)	(0.097)	(0.258)
Clay (1 =Yes;0 =Otherwise)	–0.065	0.014	0.068
	(0.083)	(0.102)	(0.247)
Source of irrigation: (baseline=surface water)			
Underground (1 =Yes;0 =Otherwise)	-0.084	-0.315***	0.556*
	(0.083)	(0.110)	(0.310)
No irrigation (1 =Yes;0 =Otherwise)	0.012	-0.201*	0.456
	(0.106)	(0.116)	(0.406)
Distance from plot to house (km)	0.023	0.089**	–0.142*
	(0.033)	(0.038)	(0.080)
Gender of respondent (1 =Male;0 =Female)	0.0715	–0.084	0.616***
	(0.0905)	(0.106)	(0.214)
Age of respondent (years)	–0.007**	0.001	0.019***
	(0.003	(0.004)	(0.007)
Education of respondent (years)	0.020**	0.030***	–0.047**
	(0.009)	(0.011)	(0.023)
Number of family members	0.032**	0.060***	0.099
	(0.015)	(0.020)	(0.049)
Share of family members with off-farm work (%)	–0.002*	–0.004**	0.010***
	(0.001)	(0.002)	(0.003)
Farm size (ha/person)	0.191*	–0.054	1.119**
	(0.113)	(0.104)	(0.499)
Distance to the nearest agricultural shop (km)	–0.001	0.022***	–0.107***
	(0.007)	(0.008)	(0.021)
Drought mitigation support (1 =Yes;0 =No)	-0.152	–0.062	0.829***
	(0.092)	(0.119)	(0.284)
Share of irrigable land in the village	–0.106	0.363**	–1.001***
	(0.133)	(0.154)	(0.327)
Agricultural insurance (1 =Yes;0 =No)	-0.031	0.115	-0.427
	(0.117)	(0.160)	(0.356)
Drought year (1 =Yes;0 =Otherwise)	0.002	–0.010	–0.035
	(0.051)	(0.064)	(0.126)
Township dummies	Controlled	Controlled	Controlled
Constant	–0.609**	-1.843***	–3.639***
	(0.320)	(0.380)	(0.885)
ρ_1 / ρ_0		0.439***	–0.145
		(0.180)	(0.247)
N		3390	
Wald χ^2		34,083.97***	
Wald χ^2 test of independent equations ($\rho_1 = \rho_0 = 0$)		4.85*	

Notes: a. The average drought-severity perception of other farmers in the same village is used to instrument for the variable "Drought-severity perception". b. 414 observations are dropped because successes are perfectly predicted. c. *, **, *** denote levels of statistical significance at 10%, 5%, and 1%, respectively. d. Robust standard errors are reported in parentheses.

among farmers that perceive increasing drought-severity and those that perceive the same or declining drought-severity, respectively. The 7.7% difference is statistically significant at 1%. In drought years, the same pattern is observed: the use rate is 8% higher among perceivers and the difference is statistically significant at 1%.

Unlike DTV use, irrigation use varies with weather conditions. Among all maize plots with access to irrigation, the share of irrigated plots is 3% higher in drought years. The difference is statistically significant at the 10% level and provides some support for treating irrigation as an *ex-post* adaptation to drought in maize production. Non-perceivers are more likely to use irrigation as an *ex-post* adaptive strategy. Among perceivers, the shares of irrigated plots do not differ much between normal and drought years. The share of irrigated plots among non-perceivers is 8.4% higher in drought years than normal years. The difference is statistically significant at 1% level.

The decisions regarding *ex-post* and *ex-ante* adaptations might be correlated. In both normal and drought years, DTV non-users irrigated a larger share of their plots than users. The difference, however, is only statistically significant in normal years and can be mostly attributed to farmers significantly cutting back irrigation on plots with DTVs in normal years. Among plots without DTVs, the irrigated share is only 1.8% lower in normal years than drought years and the difference is not statistically significant. In contrast, among plots with DTVs, the irrigated share is 7.2% lower and the difference is statistically significant at 5%. These observations also indicate that the effects of the *ex-ante* DTV use (and maybe other *ex-ante* strategies) on the *ex-post* irrigation use work mostly to reduce irrigation. This is probably because, in areas with severe water shortages, such as north China, farmers often do not have the option to increase irrigation even in normal years.

3.2. Estimation results

3.2.1. Farmers' drought-severity perceptions and the use of DTVs

Table 1 reports the estimation results of the models for DTV use. The results of estimating ESPM with FIML are reported in columns 2–4 corresponding to Eqs. (2.1), (2.2a), and (2.2b). For both the probit model and ESPM, the Wald χ^2 test statistic is statistically significant and different from zero, suggesting the joint significance of all explanatory variables.

The test results justify the use of ESPM. The Wald χ^2 test of independent equations rejects the null hypothesis of the joint independence of Eqs. (2.1), (2.2a), and (2.2b). Thus, the use of ESPM with FIML is more efficient than estimating the equations separately. In particular, the estimated correlation between the errors of Eqs. (2.1) and (2.2a), ρ_1, is statistically significant and is 0.439 in magnitude. This provides empirical evidence of a sample selectivity bias as drought-severity perception and DTV use decisions are correlated, at least among perceivers. Estimation should thus account for such endogenous switching.

Column 2 in Table 1 reports the estimation results for the impact on farmers' perceptions denoted in Eq. (2.1). The results show a strong influence of peer perceptions on a farmer's drought-severity perception. The IV coefficient, which is the average of the other farmers' perceptions in the same village, is positive and statistically significant at 1%. It is also the largest compared to coefficients of other explanatory variables. Several farm and farmer characteristics also shape farmers' drought-severity perceptions. Having loam soil reduces the likelihood of increasing drought-severity perceptions because better soil reduces the negative impacts of past droughts. Older farmers are less likely to perceive increasing drought-severity. Education has the opposite effect on perception. Younger and more educated farmers may be more

Table 2
Average treatment effect of increasing drought-severity perceptions on the use of drought-tolerant varieties.

Categories		ATT[a]	Absolute *t*-value
All sample		0.081 * **	12.012
Access to irrigation			
Yes		0.075 * **	10.258
No		0.098 * **	6.379
Weather conditions			
Normal year		0.082 * **	8.587
Drought year		0.080 * **	8.397
Farm size			
Small	(0–0.09 ha/person)	-0.002	0.202
Medium	(0.09–0.2 ha/person)	0.031 * **	3.278
Large	(> 0.2 ha/person)	0.225 * **	18.413
Drought-mitigation support			
Yes		0.068 * **	8.716
No		0.149 * **	15.170
Distance from plot to house			
Near	(0–0.5 km)	0.049 * **	5.795
Medium	(0.5–1 km)	0.076 * **	6.099
Far	(> 1 km)	0.153 * **	9.049

Note: a. Average treatment effect on the treat. b. *, **, and *** denote levels of statistical significance at 10%, 5%, and 1%, respectively.

informed and aware of the notion of climate change, and thus, pay more attention to changes in drought-severity. Farmers in larger families are more likely to perceive increasing drought-severity. As the coefficient measures the effect of one additional member and is not large, the practical impact of family size on perceptions is unlikely to be large. Farm size is positively correlated with farmers' increasing drought-severity perception. This may be because larger farms are more exposed to variations in weather conditions and experience larger negative impacts of weather shocks. Thus, any changes in weather conditions may be more evident to farmers with larger farms. The family members' share with off-farm work is negatively correlated with farmers' increasing drought-severity perception. Off-farm employment may reduce the likelihood of increasing drought-severity perception in several ways. It may divert farmers' attention away from their farms. Income from off-farm work can also offset some of the negative drought impacts. One surprising result is that drought-mitigation support does not seem to influence farmers' perception. Perhaps, providing information about climate change is not part of the extension services currently offered in rural China.

The results of factors that may drive DTV use justify the use of an endogenous switching model (Table 1, columns 3 and 4). The signs, magnitudes, and/or levels of statistical significance of the coefficients of many explanatory variables differ between perceivers and non-perceivers. The biggest differences lie in the effects of gender, farm size, and the availability of drought-mitigation support. The coefficients of these variables are small and not statistically significant among perceivers but much larger and statistically significant among non-perceivers. Increasing drought-severity perception makes male and female farmers equally likely to use DTVs. It also makes farmers with larger or smaller farms equally likely to use DTVs. Farmers are likely to use DTVs regardless of the availability of drought-mitigation support. In contrast, among non-perceivers, male farmers, farmers with larger farms, and farmers in villages with drought-mitigation support are more likely than others to use DTVs. Another difference is the effect of the irrigable land share in the village. Its coefficient is positive among perceivers but negative among non-perceivers. The difference in the coefficients is large and statistically significant. Non-perceivers in villages with better irrigation conditions are less likely to use DTVs, which makes sense. The positive correlation between better irrigation conditions and DTV use among perceivers is difficult to interpret and requires further investigation. The results confirm the existence of heterogeneity between perceivers and non-perceivers in the sample households and reveal the interactive effects between drought-severity perception and other explanatory variables.

Table 3
Estimation results of drought-severity perception and irrigation (only plots with access to irrigation).

Dependent variable	Endogenous switching probit model		
	Drought-severity Perception	Irrigation	
		Drought-severity Perception = 1	Drought-severity Perception = 0
IV for Perception[a]	2.263***		
	(0.181)		
Plot size (ha)	0.063	0.016	0.102
	(0.170)	(0.334)	2.263***
Soil type (baseline=sandy)			
Loam (1 =Yes;0 =Otherwise)	-0.237***	0.539***	(0.181)
	(0.091)	(0.166)	0.063
Clay (1 =Yes;0 =Otherwise)	-0.038	0.688***	(0.170)
	(0.093)	(0.169)	(0.245)
Source of irrigation: (baseline=surface water)			
Underground (1 =Yes;0 =Otherwise)	0.055	0.140	0.079
	(0.090)	(0.132)	(0.174)
Distance from plot to house (km)	-0.016	0.231***	0.153*
	(0.042)	(0.078)	(0.090)
Gender of respondent (1 =Male;0 =Female)	0.091	0.050	0.969***
	(0.101)	(0.156)	(0.336)
Age of respondent (years)	-0.007**	-0.005	0.001
	(0.003)	(0.005)	(0.007)
Education of respondent (years)	0.009	0.029*	-0.031
	(0.010)	(0.015)	(0.022)
Number of family members	0.026	0.049*	0.052
	(0.017)	(0.026)	(0.039)
Share of family members with off-farm work (%)	-0.001	0.003	-0.002
	(0.001)	(0.002)	(0.003)
Farm size (ha/person)	0.473**	0.363	-0.114
	(0.215)	(0.302)	(0.587)
Distance to the nearest agricultural shop (km)	0.006	-0.023*	0.003
	(0.010)	(0.014)	(0.022)
Drought mitigation support (1 =Yes;0 =Otherwise)	-0.049	-0.116	-0.182
	(0.101)	(0.189)	(0.243)
Share of irrigable land in the village	-0.291*	-0.296	-0.476
	(0.173)	(0.217)	(0.310)
Agricultural insurance (1 =Yes;0 =Otherwise)	-0.008	-0.073	0.641
	(0.144)	(0.458)	(0.422)
Drought year (1 =Yes;0 =Otherwise)	0.001	0.010	0.445***
	(0.057)	(0.087)	(0.122)
Township dummies	Controlled	Controlled	Controlled
Constant	-0.626*	6.326	1.028
	(0.370)	(13,278.407)	(0.812)
ρ_1 / ρ_0		0.300	0.335
		(0.284)	(0.253)
N		2571	
Wald χ^2		470.19 * *	
Wald χ^2 test of independent equations ($\rho_1 = \rho_0 = 0$)		2.80	

Notes: a. The average drought-severity perception of other farmers in the same village is used to instrument for the variable "Drought-severity perception". b. *, **, *** denote levels of statistical significance at 10%, 5%, and 1%, respectively. c. Robust standard errors are reported in parentheses.

The estimation results of the ESPM are employed to perform a counterfactual analysis to quantify the impacts of farmers' drought-severity perception on the DTV use likelihood. The ATT reported in Table 2 shows that among perceivers, the treatment of "perceiving increasing drought-severity" increases the probability of using DTVs by

Table 4
Average treatment effect of increasing drought-severity perceptions on irrigation.

		ATT[a]	Absolute *t*-value
All sample		–0.151 * **	22.943
Weather conditions			
Normal year		–0.169 * **	18.430
Drought year		–0.132 * **	14.100
Farm size			
Small	(0–0.09 ha/person)	–0.118 * **	14.292
Medium	(0.09–0.2 ha/person)	–0.173 * **	13.503
Large	(> 0.2 ha/person)	–0.165 * **	12.759
Drought-mitigation support			
Yes		–0.123 * **	18.797
No		–0.298 * **	14.112
Distance from plot to house			
Near	(0–0.5 km)	–0.139 * **	14.571
Medium	(0.5–1 km)	–0.168 * **	13.152
Far	(> 1 km)	–0.153 * **	12.134

Note: a. Average treatment effect on the treat. b. *, **, and *** denote levels of statistical significance at 10%, 5%, and 1%, respectively.

8.1%. If perceivers did not perceive increasing drought-severity, their likelihood of using DTVs would be lower by 8.1%. As currently, DTVs are used on only 26.8% of sample plots, an impact of 8.1% is large and practically important.

Table 2 also reports the effects of perceiving increasing drought-severity on DTV use by sample-subgroups. The results suggest that the effect is stronger on plots without access to irrigation. The ATTs for increasing drought-severity perception show a 9.8% and 7.5% increase in the probability of DTV use on plots without and with access to irrigation, respectively. Plots without irrigation would incur much bigger yield losses if droughts occurred. Therefore, increasing drought-severity perception is more likely to induce farmers' actions on such plots. The ATTs do not differ much between normal and drought years (8.2% versus 8.0%), providing further evidence that farmers use DTVs as an *ex-ante* adaptation strategy. The ATTs do vary with farm size. Sample farmers are divided into three equal portions based on farm size. On farms where per capita land holdings are above 0.2 ha/person (top 33%), farmers' increasing drought-severity perceptions increase the likelihood of DTV use by 22.5%. On medium-size farms where per capita land holdings range from 0.09 to 0.2 ha/person (middle 33%), the ATT is still positive but much smaller (3.1%). No effect is observed on small farms where per capita land holdings are below 0.09 ha/person (bottom 33%). As droughts would have bigger impacts on larger farms, increasing drought-severity perception is more likely to induce farmers with larger farms to act. The ATTs of increasing drought-severity perceptions are lower in villages with drought-mitigation support than those without such support (6.8% versus 14.9%). This indicates that the availability of drought-mitigation support muffles the effects of increasing drought-severity perceptions on DTV use. One possible explanation is that drought-related extension services might be focusing more on post-disaster assistance than educating farmers about climate change and offering support to establish proactive measures. Finally, the positive effects of increasing drought-severity perceptions on DTV use are larger on plots further away from home. The plots are divided into three equal portions based on their distance to farmers' houses. The ATTs of increasing drought-severity perception on plots more than 1 km away (top 33%) are almost twice that of plots closer by. One explanation is that it is more time-consuming to monitor the conditions of plots further away to assess irrigation needs. Using DTVs on those plots generate larger benefits in terms of labour time saved.

3.2.2. *Farmers' drought-severity perceptions and irrigation*

Table 3 reports the estimation results of ESPM for irrigation use on maize plots. Only plots with access to irrigation are included in the analysis. The Wald χ^2 test statistic of the model is statistically significant

Table 6
Average treatment effect of drought-tolerant varieties use on irrigation.

		ATT[a]	Absolute *t*-value
All sample		–0.275 * **	20.959
Weather conditions			
Normal year		–0.253 * **	13.849
Drought year		–0.296 * **	15.786
Farm size			
Small	(0–0.09 ha/person)	–0.181 * **	7.145
Medium	(0.09–0.2 ha/person)	–0.266 * **	7.519
Large	(> 0.2 ha/person)	–0.319 * **	19.276
Drought-mitigation support			
Yes		–0.276 * **	19.815
No		–0.267 * **	6.810
Distance from plot to house			
Near	(0–0.5 km)	–0.260 * **	12.973
Medium	(0.5–1 km)	–0.265 * **	10.881
Far	(> 1 km)	–0.305 * **	12.409

Note: a. Average treatment effect on the treat. b.*, **, and *** denote levels of statistical significance at 10%, 5%, and 1%, respectively

Table 5
Estimation results of drought-tolerant varieties use and irrigation (only plots with access to irrigation).

Categories	Probit	IV-Probit	Endogenous switching probit model		
				Irrigation	
	(1) Irrigation	(2) Irrigation	(3) Use of drought-tolerant varieties	(4) Drought-tolerant varieties use= 1	(5) Drought-tolerant varieties use= 0
Drought-tolerant varieties use (1 =Yes;0 =No)	–0.439*** (0.108)	–0.400*** (0.113)		—	—
IV for drought-tolerant varieties use[a]	—	—	2.865*** (0.285)	—	—
Drought-severity perception (1 =Yes;0 =Otherwise)	0.213*** (0.082)	—	—	—	—
IV for drought-severity perception[b]	—	-0.141 (0.299)	—	—	—
All explanatory variables in Table 5	Controlled	Controlled	Controlled	Controlled	Controlled
Obs.	2226[c]	2226[c]	2571		
Wald χ^2	765.06***	537.59***	646.69***		

Notes: a. The share of other farmers in the same village that used drought-tolerant varieties is used to instrument for the "Drought-tolerant varieties use" variable. b. The average drought-severity perception of other farmers in the same village is used to instrument for the "Drought-severity perception" variable. c. 323 (22) observations are dropped because successes (failures) are perfectly predicted. d. *** denotes the level of statistical significance at 1%. e. Robust standard errors are reported in parentheses.

Table A.1
Summary statistics of key variables.

Variable name (in *italic*) and description		Mean	Standard Deviation	Min	Max
Used drought tolerant variety		0.268	0.442	0	1
Drought year (1 =Yes;0 =Otherwise)		0.264	0.441	0	1
Normal year (1 =Yes;0 =Otherwise)		0.268	0.443	0	1
Irrigated (only plots with access to irrigation)		0.789	0.410	0	1
Drought year (1 =Yes;0 =Otherwise)		0.802	0.399	0	1
Normal year (1 =Yes;0 =Otherwise)		0.772	0.420	0	1
Plot level (1695 plots)					
Plot size (ha)		0.28	0.31	0.01	3.00
Soil type dummy variables: *Sandy* (1 =Yes;0 =Otherwise)		0.28	0.45	0	1
Loam (1 =Yes;0 =Otherwise)		0.40	0.49	0	1
Clay (1 =Yes;0 =Otherwise)		0.32	0.47	0	1
Source of irrigation: Surface water		0.266	0.442	0	1
	Underground water (1 =Yes;0 =Otherwise)	0.493	0.500	0	1
	No-irrigation (1 =Yes;0 =Otherwise)	0.231	0.428	0	1
Dis. House	(Distance from plot to house in km)	0.89	0.86	0	8.00
Irri. Access	(A plot has access to irrigation)	0.758	0.428	0	1
Farmer and farm level (1058 farmers)					
Perception	(Farmers' perceptions of drought severity, 1 = Increased; 0 = Same, Decreased or Don't know)	0.71	0.45	0	1
Male	(Gender of the respondent is male)	0.89	0.32	0	1
Age	(Age of the respondent in years)	51.70	10.38	23.00	86.00
Education	(Years of schooling the respondent)	6.70	3.05	0.00	16.00
Family size	(Number of family members)	4.44	1.83	1	12
Off-farm work (%)	(Share of family members with off-farm work)	28.82	24.15	0	100
Farm size	(Per capita land holding in ha/person)	0.23	0.31	0.01	5.88
Dis. Shop	(Distance from house to nearest agriculture supply shop in km)	4.00	5.41	0	50.00
Village level (123 villages)					
Support	(Drought mitigation support is available in the village)	0.85	0.35	0	1
Insurance	(Agricultural insurance support in the village)	0.911	0.286	0	1
Irrigable land	(Share of irrigable land in the village)	0.60	0.36	0	1

Source: Authors' survey

and different from zero, indicating the joint significance of all explanatory variables. However, the Wald χ^2 test of independent equations fails to reject the null hypothesis of the joint independence of the equations. Neither of the two estimated correlations between equations (ρ_0 and ρ_1) is statistically significant, suggesting that the hypothesis of no selection bias for farmers' drought-severity perception in explaining irrigation cannot be rejected. Therefore, although ESPM use is valid, it does not necessarily increase estimation efficiency relative to an approach that estimates Eqs. (2.1), (2.2a), and (2.2b) separately.

Most estimates of parameters in the selection Eq. (2.1) for the ESPM for irrigation (Table 3, column 1) are consistent with those for DTV use (Table 1, column 2). One interesting difference is the coefficient of the irrigable land share in the village is negative and statistically significant in Table 3 but not in Table 1. This means that irrigation conditions only shape drought-severity perceptions for plots that have access to irrigation. Better irrigation conditions reduce the likelihood of perceiving increasing drought-severity, perhaps because irrigable plots in villages with better irrigation conditions are more sheltered from the negative drought impacts.

There are fewer differences in the coefficients of irrigation equations between perceivers and non-perceivers (Table 3, columns 2 and 3) than those observed for DTV equations reported in Table 1. For both perceivers and non-perceivers, farmers are more likely to irrigate loam and clay plots instead of sandy plots, probably due to higher percolation rates on sandy plots. For both groups, the distance from a plot to a farmer's house is positively correlated with the probability of irrigation. One significant difference lies in the gender effect. Among non-perceivers, a male household head increases the irrigation likelihood while no correlation is observed between gender and irrigation among perceivers. The same difference is observed in Table 1. Another significant difference is while current weather conditions do not affect the irrigation likelihood among perceivers, drought occurrence increases irrigation among non-perceivers. The coefficient of the dummy indicating a drought year is negative and statistically significant in the equation for non-perceivers. This difference is consistent with the observation from Table A.4 in Appendices A that non-perceivers are more likely than perceivers to use irrigation as an *ex-post* adaptive strategy.

Table 4 reports the ATTs of perceiving increasing drought-severity on irrigation. Overall, increasing the drought-severity perception reduces irrigation probability by 15.1%. The negative effect is slightly stronger in drought years than normal years and is smaller on small farms than medium and large farms. Subgroups by the availability of drought-mitigation support present the largest differences in ATTs. The negative effect of perceiving increasing drought-severity in villages that do not have drought-mitigation support is more than twice the other villages. The differences in ATTs among plots with varying distances to farmers' houses are not statistically significant.

3.2.3. Relationship between DTV use and irrigation

Table 5 reports the estimation results of several models used to explore the DTV–irrigation decision relationship. Columns 1 and 2 are both probit models where irrigation is the outcome and DTV use is added as an explanatory variable. In column 2, the average drought-severity perception of other farmers in the same village is used to instrument for a farmer's perception. Although the coefficient of perception is positive and statistically significant in the simple probit model (column 1), in the IV-probit model (column 2), its magnitude drops to nearly zero and the statistical significance is lost. Therefore, it is most likely that after the use of DTVs is controlled for, drought-severity perception does not have additional predictive powers for variations in irrigation decisions. This is because that irrigation is more likely to be used as an *ex-post* adaptation strategy. Irrigation decisions are made contingent on field and weather conditions during the growing season, not on perceptions formed before the growing season. In both columns 1 and 2, the coefficients of the variable indicating DTV use are negative and statistically significant, pointing to a negative correlation between DTV use and irrigation on maize plots.

The ESPM with FIML estimation is presented in columns 3–5. Column 3 is the selection equation for DTV use. Columns 4 and 5 are the switching equations on irrigation for DTV users and non-users. Perception is not included because it does not seem to have predictive powers once DTV use is controlled for. The share of other farmers in the same village that used DTVs is used to instrument for a farmer's DTV use. The coefficient of the IV is positive and statistically significant at 1% (Table A.5 in Appendices A). The results of ESPM in columns 3–5 could be further used to conduct a counterfactual analysis of the impact of DTV use on irrigation. Table 6 reports the ATTs computed from the estimation results of the ESPM. The direction of the ATTs is consistent with that in the simple probit model. The treatment of "using DTVs" decreases the probability of irrigation by 27.5%.

According to the results in Table 2, 4–6 together, the relationships

Table A.2
Differences in explanatory variables between users and non-users of drought-tolerant varieties and irrigation.

	Drought-tolerant varieties				Irrigation (Only plots with access to irrigation)			
	Normal year		Drought year		Normal year		Drought year	
	Users	Non-users	Users	Non-users	Users	Non-users	Users	Non-users
Plot level								
Plot size (ha)	0.43	0.23 * **	0.43	0.23 * **	0.25	0.27	0.27	0.24
Soil type:								
Sandy(1 =Yes;0 =Otherwise)	0.35	0.26 * **	0.35	0.26 * **	0.28	0.24	0.28	0.26
Loam (1 =Yes;0 =Otherwise)	0.38	0.40	0.37	0.40	0.37	0.41	0.36	0.44 * *
Clay (1 =Yes;0 =Otherwise)	0.28	0.34 * *	0.28	0.34 * *	0.34	0.35	0.35	0.30 *
Source o irrigation:								
Surface water (1 =Yes;0 =Otherwise)	0.158	0.305	0.156	0.302	0.316	0.494	0.318	0.447
Underground water (1 =Yes;0 =Otherwise)	0.457	0.505	0.460	0.506	0.684	0.506	0.682	0.553
No-irrigation (1 =Yes;0 =Otherwise)	0.384	0.189	0.383	0.191	-	-	-	-
Distance from plot to house (km)	1.09	0.81 * **	1.09	0.81 * **	0.85	0.71 * **	0.86	0.65 * **
Irrigation access (1 =Yes;0 =Otherwise)	0.62	0.81 * **	0.62	0.81 * **				
Farmer and farm level								
Gender of respondent (1 =Male;0 =Female)	0.93	0.87 * **	0.93	0.88 * **	0.87	0.90 *	0.87	0.89
Age of respondent (years)	49.73	52.84 * **	49.67	52.84 * **	52.76	52.88	52.67	52.83
Education of respondent (years)	6.80	6.66	6.82	6.66	6.74	6.50	6.71	6.61
Number of family members	4.26	4.52 * *	4.20	4.54 * **	4.42	4.58	4.42	4.61
Share of family members with off-farm work (%)	24.82	30.23 * **	24.47	30.33 * **	29.72	28.47	29.63	28.61
Farm size (ha/person)	0.35	0.19 * **	0.36	0.19 * **	0.22	0.21	0.23	0.18 * *
Distance to the nearest agricultural shop (km)	5.80	3.10 * **	5.89	3.08 * **	3.04	3.73 * *	3.06	3.76 * *
Village level								
Drought mitigation support (1 =Yes;0 =Otherwise)	0.90	0.83 * **	0.90	0.83 * **	0.84	0.88 *	0.83	0.81 * **
Agricultural insurance (1 =Yes;0 =Otherwise)	0.96	0.89 * **	0.96	0.89 * **	0.89	0.97 * **	0.90	0.95 * *
Share of irrigable land in the village	0.47	0.68 * **	0.48	0.67 * **	0.79	0.60 * **	0.78	0.56 * **
Observations of plots	454	1241	448	1247	993	293	1032	255

Note: a. *, **, *** denote the level of statistical significance of a mean-comparison test is at 10%, 5%, and 1%, respectively. b. The differences in means of most variables between drought-tolerant varieties users and non-users are statistically significant at either 5% or 1%. This is the case for both normal and drought years. The results indicate possible correlations between these variables and the use of drought-tolerant varieties. c. Between irrigated and rain-fed maize plots, the differences in means are statistically significant for fewer variables but the results still reveal some possible correlations.

Table A.3
Falsification test of the validity of the selection instrument using Probit model.

Dependent variable	Drought-severity perception		Drought-severity perception = 0			
			Drought-tolerant varieties use		Irrigation	
IV for the perception[a]	2.974***	2.306***	0.304	0.372	-0.157	-0.530
	(0.110)	(0.164)	(0.193)	(0.525)	(0.175)	(0.3272)
Other variables		Controlled		Controlled		Controlled
Township dummies		Controlled		Controlled		Controlled
Constant	-1.441***	-0.642**	-0.957***	-3.706***	0.423***	0.936
	(0.074)	(0.328)	(0.109)	(1.054)	(0.097)	(0.814)
N	3390	3284[a]	1044	708[b]	1044	618[c]
Pseudo R^2	0.210	0.219	0.115	0.423	0.369	0.244
LR χ^2	880.40***	897.36 * **	2.49***	367.71 * **	0.81***	177.50 * **

Note: a. The average drought-severity perception of other farmers in the same village is used to instrument for the variable "Drought-severity perception". b. 106 observations are dropped because successes are perfectly predicted. c. 330 (6) observations are dropped because failures (successes) are perfectly predicted. d. 214 (22) observations are dropped because successes (failures) are perfectly predicted. e. * , * *, * ** denote levels of statistical significance at 10%, 5%, and 1%, respectively.

among drought-severity perception, DTV use, and irrigation can be summarised as follows. Perceiving increasing drought-severity increases DTV use likelihood and reduces irrigation likelihood in maize production. Further, it is likely that the negative effect of perception on irrigation mainly works through the negative correlation between using DTVs and irrigation.

Table 6 also reports the ATTs of using DTVs on irrigation by sample-subgroups. The results suggest the negative effect is stronger in normal years than in drought years (25.3 versus 29.6% reduction irrigation likelihood). This is consistent with the observation in Table A.4 in Appendices A that DTV non-users irrigate a larger share of their plots than users but the difference is statistically significant only in normal years. This finding may be more important for areas that use groundwater. Less water use in normal years means more water would be available in aquifers during drought years. The negative effect DTV use on irrigation is stronger on large farms than on medium or small farms. The ATTs do not differ much between villages with and without drought-mitigation support and are larger in magnitudes on plots further away from farmers' houses.

3.3. Robustness check

To confirm the stability of the main findings of this study, we further conduct a set of robustness checks as follows. First, we re-estimate the

Table A.4
Comparisons of the use of adaptation strategies between normal and drought years and by farmers' perception of drought severity.

	Share of farmers using drought-tolerant varieties (%)			Share of farmers using irrigation (%) (Only plots with access to irrigation)		
	Normal year (N)	Drought year (D)	Difference (N - D)[a]	Normal year (N)	Drought year (D)	Difference (N - D)[a]
All sample plots	26.78	26.43	0.35	77.18	80.19	-3.01 *
Perceptions of increasing drought severity						
Yes	29.16	28.90	0.26	79.11	79.42	-0.31
No	21.46	20.88	0.58	73.30	81.73	-8.43 * **
Difference (Yes-No)[a]	7.70 * **	8.02 * **		5.81 * *	-2.31	
Drought tolerant varieties use						
Yes				72.14	79.34	-7.20 * *
No				78.59	80.42	-1.83
Difference (Yes -No)[a]				-6.45 * *	1.08	

Note: a. The Difference columns and rows report the results of mean-comparison tests. b. * , * * and * ** denote levels of statistical significance at 10%, 5% and 1%, respectively.

Table A.5
Farmers' perceptions of drought severity and the use of drought-tolerant varieties and irrigation.

Perceptions of drought severity	Sample size		Share of farmers using drought-tolerant varieties (%)	Share of farmers using irrigation (%)
	Freq.	Percent (%)		
Increased#	754	71.27	29.03	58.23
Decreased	114	10.78	18.95 * **	66.05 * **
Same	182	17.20	22.17 * **	61.79 *
Don't know	8	0.76	28.57	64.29

Note: a. # reference group of mean-comparison tests. b. *, ** and *** denote levels of statistical significance at 10%, 5% and 1%, respectively.

Table A.6
Results of robustness check.

a. Exclude samples from Jiangsu province			
Categories	Impact of increasing drought-severity perceptions on drought-tolerant varieties use	Impact of increasing drought-severity perceptions on irrigation	Impact of drought-tolerant varieties use on irrigation
ATT[a]	0.039 * **	-0.162 * **	-0.361 * **
b. Alternative estimations & alternative specification of irrigation variable			
Alternative estimations	Two steps & Control function approach	Endogenous treatment Poisson regression	Endogenous treatment Poisson regression
Alternative specifications		Irrigation times	Irrigation times
ATT	0.239 * **	-0.700 * **	-0.675 * **

Note: a. Average treatment effect on the treat. b. *, ** and *** denote levels of statistical significance at 10%, 5% and 1%, respectively.

impacts of drought perception on using DTVs and irrigation by adjusting samples. Considering the geographic distribution of sample provinces in this study, all provinces are located in northern China in addition to Jiangsu province. Thus, we drop the samples from Jiangsu and re-estimate the empirical models. As shown in Table A.6 in Appendices A, for the samples from all northern provinces, the impact of drought perception on DTVs use gets smaller than that of previous results, while both drought perception and DTVs use have more negative impacts on irrigation than before. Hence, although the magnitudes of ATTs changed, their significances and impact directions are completely same with our main results. These results not only confirm the stability of the main findings but also imply heterogeneous effects of farmers drought perceptions on adaptation strategies in different regions.

Second, the impact of increasing drought-severity perceptions on DTVs use is re-estimated by employing the two steps and control function approach (Table A.6 in Appendices A). The marginal effect of drought perception on DTVs use is significantly positive, consistent with the ATT of main results. However, the combination approach of two steps and control function cannot control for the potential selection bias; accordingly, here, the marginal effect of increasing drought-severity perceptions on DTVs use is over-estimated.

Third, the irrigation model is re-estimated by using a variable of irrigation count, whilst the endogenous treatment Poisson regression is further employed. As shown in Table A.6 in Appendices A, the ATTs of drought perception and DTVs use on irrigation count are both significantly negative. The results are in line with the main results and further confirm that perceiving increasing drought-severity and using DTVs can reduce the use of irrigation.

4. Conclusions

In response to drought, maize farmers in north China may have both *ex-ante* and *ex-post* adaptations, while this study focuses on two adaptation strategies: the *ex-ante* adoption of DTVs and the *ex-post* use of irrigation. Farmers' perception of increasing drought-severity can increase the probability of using DTVs by 8.1% and lower the probability of irrigation by 15.1% on maize plots. However, once DTV use is controlled for, perception does not seem to have additional predictive powers for irrigation, implying that irrigation decisions are made not on perceptions formed before the growing season. Instead, DTV use reduces the probability of irrigation by 27.5%, confirming that DTV use is effective for saving irrigation water.

This study contributes to the existing literature of the impacts of farmers' perceptions on their adaptation to climate change. As shown in most studies (Abid et al., 2020; Brüssow et al., 2019; Dang et al., 2019), farmers who perceived climate change are more likely to take adaption actions. Our study provides additional evidence for the positive linkage between perceptions and adaptation behaviour. Moreover, this study distinguished *ex-ante* and *ex-post* adaptations and found out perceptions may have different impacts on different types of adaptation measures. Similar to our results, Brüssow et al. (2019) found that farmers in Tanzania who perceived climate change are more likely to take short-term adaptations rather than investment-intensive method, such as building irrigation system. Hou et al. (2017) found that farmers perceiving increasing drought are more likely to adopt water-saving technologies, but they did not distinguish ex-ante and ex-post adaptations. This paper also advanced the literature by setting up a conceptual framework to describe the linkages between perceptions and different types of adaptation measures. Few existing studies presented theoretical models.

The findings of this study have three policy implications. First, the positive effect of perceiving increasing drought-severity on DTV use suggested that policy makers can improve adoption of DTV through increasing farmers' perceptions of climate change. Less than 30% of our sample plot used DTVs, indicating large scope for boosting its use. Second, our results also suggest that several channels that could improve farmers' perceptions. For example, educating influential farmers in the village about the changes in weather conditions would pay off, as our results show that peer perceptions matter. Another example, interventions that target large farms may be more effective. Third, the linkage between *ex-ante* and *ex-post* adaptation measures suggest that it is of great important to distinguish types of adaptation measures as limited adaptation resources could be allocated efficiently. In our example, DTVs can reduce use of irrigation water. This has significant policy implications, especially for the areas with severe water shortage. Moreover, in those areas, targeting larger farms and villages where land is distributed more sparsely and further away from farmers' houses to promote DTVs may achieve a larger reduction in irrigation water use. Under the constraint of water resource, the water saving by using DTVs actually has huge external positive effect on the sustainability of economic, social development and environment.

Finally, we call for further study on evaluating the optimal strategy mix, i.e. how to allocate adaptation funding and efforts among different types of adaptation measures. In our sample, almost 80% of irrigable sample plots are irrigated, while less than 30% use *ex-ante* adaptations such as DTVs. If *ex-ante* adaptations can better hedge farmers against weather risks at lower costs compared to those of *ex-post* adaptations, more extension efforts and financial resources should be allocated towards *ex-ante* adaptations.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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Appendices A.

See Appendix Tables A.1-A.6.

Appendices B.

Theoretical framework

Referring the studies of Foudi and Erdlenbruch (2012), Lehmann, N. and Finger (2014) and Jianjun et al. (2015), this study develops a conceptual model to capture the impacts of farmers' drought-severity perceptions on their *ex-ante* and *ex-post* adaptations based on the expected utility model. In practice, farmers have many adaptation strategies to drought risks, for instance, adopting new technology, planting new crop varieties, purchasing crop insurance, crop diversification, investing in irrigation infrastructure (Jianjun et al., 2015). This study focuses on the use of drought-tolerant varieties and irrigation, as they are the most direct related measures with water. The study on these two strategies helps better understand the design of agricultural water-saving strategies under drought risks. Thus, the use of drought-tolerant varieties (DTVs) of maize is treated as an *ex-ante* adaptation as this decision is made before the start of the growing season, and is *ex-ante* relative to the drought occurring in the growing season. In contrast, irrigation is an *ex-post* adaptation to drought, because the irrigation decision is made according to actual weather conditions. Sufficient precipitation could ensure maize is completely rain-fed without the need for irrigation. If a drought occurs, then farmers will decide whether to irrigate. Thus, in maize production, irrigation decisions can be treated as an *ex-post* adaptation to drought. Hence, the conceptual model can be established through two stages.

The ex-ante choice of maize variety

In the first stage, a decision model on DTV adoption in maize farming is developed based on the expected utility model and the household model of agricultural production. The expected utility (u_i) is assumed to be determined by the profit of the maize farming at the i^{th} plot and its maximisation problem can be written as follows:

$$\mathrm{Max}\mathrm{u}_i = \mathrm{Max}\left\{\int [\mathbf{y}_i - c(\mathbf{k}_i) f(\mathbf{y}_i) d\mathbf{y}\right\} \tag{B.1}$$

$$s.t.\mathbf{y}_i = \mathbf{y}(\mathbf{k}_i | L_i, I_i)$$

$$\sum\nolimits_{i=1}^{2} k_i = 1$$

where L_i represents the planting area of maize farming at the i^{th} plot available to the farmer, while I_i denotes the irrigation condition of the i^{th} plot. The vector $\mathbf{k}_i = (k_{i1}, k_{i2})$, where k_{i1} and k_{i2} are dummy variables representing the variety use of the i^{th} plot (k_{i1}=1 denotes DTV; k_{i2}=1 denotes conventional variety). $\mathbf{y}_i$ is a vector of outputs corresponding to $\mathbf{k}_i$ given the planting area of maize (L_i) and the irrigation condition (I_i) of the i^{th} plot, while $c(\mathbf{k}_i)$ is the cost function corresponding to $\mathbf{k}_i$. In addition to the used variety ($\mathbf{k}_i$), the cost function ($c(\mathbf{k}_i)$) also depends on the variable inputs and the corresponding prices.

$f(\mathbf{y})$ is the farmer's subjective probability density function for $\mathbf{y}_i$, which is assumed to be solely related to the weather conditions (w_t) in the coming crop season (Bai et al., 2015). We assume that all maize farmers in the same location face the same market prices of maize, maize varieties, and inputs in the observation year. According to our observations, as no significant differences exist in the market prices of DTVs and conventional varieties, the price variables are omitted in the utility function (1).

As farmers do not know the weather conditions in the coming crop season (w_t), they make the decision on **x** based on their prediction of the weather conditions. Here, we assume that farmers' prediction of weather conditions in the coming crop season ($\widehat{w_t}$) can be expressed as

$$\widehat{w_t} = g(w_{-t}, P) \tag{B.2}$$

where w_{-t} denotes the real weather conditions in previous years, while P represents farmers' perceptions of the weather condition change in previous years.

By incorporating the weather condition prediction function (B.2) into the maximisation problem (B.1), the optimal variety choice ($\mathbf{x}_{it}{}^*$) of the i^{th} plot can be conceptually derived as

$$\mathbf{x}_{it}{}^* = z(w_{-t}, P, c, L_i, I_i) \tag{B.3}$$

where the real weather conditions in previous years (w_{-t}) could be omitted as there is an implicit assumption that all farmers in the same location (g) faced the same weather conditions in previous years. Given this study's focus on drought adaptations, the perception of a change in weather conditions (P) here is proxied by the drought-severity perception (P'). The optimal variety choice of the i^{th} plot for using DTV can then be simplified as:

$$k_{i1}{}^* = z'(P', c, L_i, I_i, g) \tag{B.4}$$

where$k_{i1}{}^* = 1$ indicates that the maize farmer adopts DTV at the i^{th} plot, otherwise 0. The formula (B.4) reveals that the *ex-ante* choice of using DTV on the i^{th} plot depends on farmers' perceptions of drought severity, the input costs (c) of DTV and conventional variety, the plot area (L), irrigation condition (I) and the location (g) of the i^{th} plot.

The ex-post choice of irrigation

In the second stage, the decision on irrigation is made according to the previous decision of DTV adoption and actual weather conditions. Hence, in this stage, the expected utility maximisation (u_i) of the maize farming of the i^{th} plot can be modified as:

$$\text{Max}u_i = \text{Max}\left\{ \int [\mathbf{y}_i - c'(k_{i1}{}^*, \boldsymbol{i}_i)] g(\mathbf{y}_i) d\mathbf{y} \right\} \tag{B.5}$$

$$s.t.\mathbf{y}_i = \mathbf{y}(k_{i1}{}^*, \boldsymbol{i}_i | L_i, I_i)$$

$$\sum\nolimits_{m=1}^{2} i_{im} = 1$$

where i_{i1} and $i_{i2}$are dummy variables representing the irrigation decision of the i^{th} plot (i_{i1}=1 denotes irrigate; i_{i2}=1 denotes do not irrigate) that constitute $\boldsymbol{i}_i = (i_{i1}, i_{i2})$. $\mathbf{y}_i$ is a vector of outputs corresponding to $k_{i1}{}^*$ and $\boldsymbol{i}_i$ given the area (L_i) and irrigation condition (I_i) of the i^{th} plot. $c'(k_{i1}{}^*, \boldsymbol{i}_i)$ is the cost function corresponding to $k_{i1}{}^*$ and $\boldsymbol{i}_i$. The farmer's subjective probability density function $g(\mathbf{y})$ is assumed to be related to weather conditions $\dot{w}_t$, which includes both the actual weather conditions prevailing in the crop growing season (w_{t-1}) and the prediction in the coming crop season ($\widehat{w_t}$).

The optimal choice of **i** could, thus, be conceptually expressed as:

$$\mathbf{i}_t{}^* = l(w_{-t}, w_{t-1}, P', c', k_{i1}{}^*, L_i, I_i) \tag{B.6}$$

where both the weather conditions in previous years (w_{-t}) and the actual weather conditions occurring in the crop growing season (w_{-t}) could be neglected by assuming weather conditions remain unchanged at the same location (g). The irrigation decision on the i^{th} plot can be obtained and written as a function (B.7) by incorporating the function (B.4) into the function (B.6):

$$i_{i1}{}^* = l'(P', \text{c}, c', L_i, I_i, g) \tag{B.7}$$

Hence, the drought-severity perceptions determine the *ex-post* irrigation decision of the i^{th} plot. Also, the *ex-post* irrigation decision is affected by the input costs of maize farming using DTV and conventional variety at the i^{th} plot (c), the input costs of irrigation at the i^{th} plot (c'), the planting area (L_i) and irrigation condition of the i^{th} plot I_i, and the location g.

References

Abid, M., Ali, A., Raza, M., Mehdi, M., 2020. Ex-ante and ex-post coping strategies for climatic shocks and adaptation determinants in rural Malawi. Clim. Risk Manag 27, 100200. https://doi.org/10.1016/j.crm.2019.100200.

Akter, S., Bennett, J., 2011. Household perceptions of climate change and preferences for mitigation action: the case of the Carbon Pollution Reduction Scheme in Australia. Clim. Change 109, 417–436. https://doi.org/10.1007/s10584-011-0034-8.

Alam, G.M.M., Alam, K., Mushtaq, S., 2016. Influence of institutional access and social capital on adaptation decision: Empirical evidence from hazard-prone rural households in Bangladesh. Ecol. Econ. 130, 243–251. https://doi.org/10.1016/j.ecolecon.2016.07.012.

Ayuya, O.I., Gido, E.O., Bett, H.K., Lagat, J.K., Kahi, A.K., Bauer, S., 2015. Effect of certified organic production systems on poverty among smallholder farmers: Empirical evidence from Kenya. World Dev. 67, 27–37. https://doi.org/10.1016/j.worlddev.2014.10.005.

Báez, J.E., Fuchs, A., Rodríguez-Castelán, C., 2017. Shaking Up Economic Progress: Aggregate Shocks in Latin America and the Caribbean, Latin America and the Caribbean Regional Study. World Bank Publications, Washington DC. https://doi.org/10.1596/28892.

Barbier, E.B., Hochard, J.P., 2018. The impacts of climate change on the poor in disadvantaged regions. Rev. Environ. Econ. Policy 12, 26–47. https://doi.org/10.1093/reep/rex023.

Brüssow, K., Gornott, C., Faße, A., Grote, U., 2019. The link between smallholders' perception of climatic changes and adaptation in Tanzania. Climatic Change 157 (3), 545–563. https://doi.org/10.1007/s10584-019-02581-9.

Calzadilla, A., Zhu, T., Rehdanz, K., Tol, R.S.J., Ringler, C., 2013. Economy wide impacts of climate change on agriculture in Sub-Saharan Africa. Ecol. Econ. 93, 150–165. https://doi.org/10.1016/j.ecolecon.2013.05.006.

Chen, H., Wang, J., Huang, J., 2014. Policy support, social capital, and farmers' adaptation to drought in China. Glob. Environ. Chang 24, 193–202. https://doi.org/10.1016/j.gloenvcha.2013.11.010.

Comoé, H., Finger, R., Barjolle, D., 2014. Farm management decision and response to climate variability and change in Côte d'Ivoire. Mitig. Adapt. Strat. G. L 19 (2), 123–142. https://doi.org/10.1007/s11027-012-9436-9.
Dang, H.L., Li, E., Bruwer, J., Nuberg, I., 2014. Farmers' perceptions of climate variability and barriers to adaptation: lessons learned from an exploratory study in Vietnam. Mitig. Adapt. Strat. G. L. 19, 531–548. https://doi.org/10.1007/s11027-012-9447-6.
Dang, H.L., Li, E., Nuberg, I., Bruwer, J., 2019. Factors influencing the adaptation of farmers in response to climate change: A review. Clim. Dev. 11, 765–774. https://doi.org/10.1080/17565529.2018.1562866.
Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T., Yesuf, M., 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. Glob. Environ. Chang 19, 248–255. https://doi.org/10.1016/j.gloenvcha.2009.01.002.
Deressa, T.T., Hassan, R.M., Ringler, C., 2011. Perception of adaptation to climate change by farmers in the Nile basin of Ethiopia. J. Agr. Sci. -Camb. 149, 23–31. https://doi.org/10.1017/S0021859610000687.
Di Falco, S., Veronesi, M., Yesuf, M., 2011. Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. Am. J. Agr. Econ. 93, 825–842. https://doi.org/10.1093/ajae/aar006.
Ding, Y., Schoengold, K., Tadesse, T., 2009. The impact of weather extremes on agricultural production methods: Does drought increase adoption of conservation tillage practices? J. Agr. Resour. Econ. 395–411. ⟨http://www.jstor.org/stable/41548424⟩.
Fosu-Mensah, B.Y., Vlek, P.L., MacCarthy, D.S., 2012. Farmers' perception and adaptation to climate change: a case study of Sekyedumase district in Ghana. Environ. Dev. Sustain 14 (4), 495–505. https://doi.org/10.1007/s10668-012-9339-7.
Foudi, S., Erdlenbruch, K., 2012. The role of irrigation in farmers' risk management strategies in France. Eur. Rev. Agric. Econ. 39 (3), 439–457. https://doi.org/10.1093/erae/jbr024.
Giles, J., 2000. Is life more risky in the open? Household risk-coping and the opening of China's labor markets. J. Dev. Econ. 81, 25–60. https://doi.org/10.1016/j.jdeveco.2005.04.006.
Gregory, C.A., Colemanjensen, A., 2013. Do high food prices increase food insecurity in the United States? Appl. Econ. Perspect. P 35, 679–707. https://doi.org/10.1093/aepp/ppt024.
Grothmann, T., Reusswig, F., 2006. People at risk of flooding: Why some residents take precautionary action while others do not. Nat. Hazards 38, 101–120. https://doi.org/10.1007/s11069-005-8604-6.
Hertel, T.W., Lobell, D.B., 2014. Agricultural adaptation to climate change in rich and poor countries: current modeling practice and potential for empirical contributions. Energ. Econ. 46, 562–575. https://doi.org/10.1016/j.eneco.2014.04.014.
Hou, L., Huang, J., Wang, J., 2015. Farmers' perceptions of climate change in China: the influence of social networks and farm assets. Clim. Res. 63, 1670–1677. https://doi.org/10.3354/cr01295.
Hou, L., Huang, J., Wang, J., 2017. Early warning information, farmers' perceptions of, and adaptations to drought in China. Clim. Change 141, 197–212. https://doi.org/10.1007/s10584-017-1900-9.
Huang, J., Wang, Y., Wang, J., 2015. Farmers' adaptation to extreme weather events through farm management and its impacts on the mean and risk of rice yield in China. Am. J. Agr. Econ. 97, 603–617. https://doi.org/10.1093/ajae/aav005.
Islam, M.A., Warwick, N., Koech, R., Amin, M.N., de Bruyn, L.L., 2020. The importance of farmers' perceptions of salinity and adaptation strategies for ensuring food security: Evidence from the coastal rice growing areas of Bangladesh. Sci. Total Environ., 138674 https://doi.org/10.1016/j.scitotenv.2020.138674.
Ji, Y., Zhong, F., Jiao, L.I., 2010. Water shortages loom as northern China's aquifers are sucked dry. Food Secur 328, 1462–1463. https://doi.org/10.1126/science.328.5985.1462-a.
Jianjun, J., Yiwei, G., Xiaomin, W., Nam, P.K., 2015. Farmers' risk preferences and their climate change adaptation strategies in the Yongqiao District, China. Land Use Policy 47, 365–372. https://doi.org/10.1016/j.landusepol.2015.04.028.
Lee, T.M., Markowitz, E.M., Howe, P.D., Ko, C.Y., Leiserowitz, A.A., 2015. Predictors of public climate change awareness and risk perception around the world. Nat. Clim. Change 5, 1014–1120. https://doi.org/10.1038/nclimate2728.
Lehmann, N., Finger, R., 2014. Economic and environmental assessment of irrigation water policies: A bioeconomic simulation study. Environ. Modell. Softw. 51, 112–122. https://doi.org/10.1016/j.envsoft.2013.09.011.
Leiserowitz, A., 2007. International public opinion, perception, and understanding of global climate change. Hum. Dev. Rep. 2008, 1–40. ⟨https://core.ac.uk/display/6248846⟩.
Leng, G., Tang, Q., Rayburg, S., 2015. Climate change impacts on meteorological, agricultural and hydrological droughts in China. Glob. Planet. Change 126, 23–34. https://doi.org/10.1016/j.gloplacha.2015.01.003.
Lokshin, M., Glinskaya, E., 2008. The effect of male migration on employment patterns of women in Nepal. World Bank Econ. Rev. 23, 481–507. https://doi.org/10.1093/wber/lhp011.
Lokshin, M., Sajaia, Z., 2011. Impact of interventions on discrete outcomes: maximum likelihood estimation of the binary choice models with binary endogenous regressors. Stata J. 11, 368–385. https://doi.org/10.1177/1536867×1101100303.
Lorenzoni, I., Pidgeon, N.F., 2006. Public views on climate change: European and USA perspectives. Clim. Change 77, 73–95. https://doi.org/10.1007/s10584-006-9072-z.
Maddison, D., 2007. The Perception of and Adaptation to Climate Change in Africa. The World Bank,, Washiongtown DC. https://doi.org/10.1596/1813-9450-4308.
Meraner, M., Finger, R., 2019. Risk perceptions, preferences and management strategies: evidence from a case study using German livestock farmers. J. Risk Res. 22 (1), 110–135. https://doi.org/10.1080/13669877.2017.1351476.
Min, S., Waibel, H., Huang, J., 2017. Smallholder participation in the land rental market in a mountainous region of Southern China: Impact of population aging, land tenure security and ethnicity. Land Use Policy 68, 625–637. https://doi.org/10.1016/j.landusepol.2017.08.033.
Oster, E., 2019. Unobservable selection and coefficient stability: Theory and evidence. J. Bus. Econ. Stat. 37 (2), 187–204. https://doi.org/10.1080/07350015.2016.1227711.
Owens, T., Hoddinott, J., Kinsey, B., 2004. Ex-Ante actions and ex-Post public responses to drought shocks: evidence and simulations from Zimbabwe. World Dev. 31, 1239–1255. https://doi.org/10.1016/S0305-750X(03)00068-8.
Parvathi, P., Waibel, H., 2016. Organic agriculture and fair trade: a happy marriage? a case study of certified smallholder black pepper farmers in India. World Dev. 77, 206–220. https://doi.org/10.1016/j.worlddev.2015.08.027.
Rashid, M.H., Afroz, S., Gaydon, D., Muttaleb, A., Poulton, P., Roth, C., Abedin, Z., 2014. Climate change perception and adaptation options for agriculture in Southern Khulna of Bangladesh. Appl. Ecol. Environ. Sci. 2, 25–31. https://doi.org/10.12691/aees-2-1-4.
Salau, E.S., Onuk, E.G., Ibrahim, A., 2012. Knowledge, perception and adaptation strategies to climate change among farmers in southern agricultural zone of Nasarawa State, Nigeria. J. Agric. Ext. 16, 199–211. https://doi.org/10.4314/jae.v16i2.15.
Shi, J., Visschers, V.H., Siegrist, M., 2015. Public perception of climate change: the importance of knowledge and cultural worldviews. Risk Anal. 35, 2183–2201. https://doi.org/10.1111/risa.12406.
Smit, B., Pilifosova, O., 2001. Adaptation to climate change in the context of sustainable development and equity. In: McCarthy, J., Canziani, O.F., Leary, N.A., Dokken, D.J., White, K.S. (Eds.), Climate Change 2001: Impacts, Adaptation and Vulnerability. Cambridge University Press, Cambridge.
Smit, B., Burton, I., Klein, R.J.T., Wandel, J., 2000. An anatomy of adaptation to climate change and variability. Clim. Change 45, 223–251. https://doi.org/10.1023/A:1005661622966.
Spence, A., Poortinga, W., Butler, C., Pidgeon, N.F., 2011. Perceptions of climate change and willingness to save energy related to flood experience. Nat. Clim. Change 1, 46–49. https://doi.org/10.1038/nclimate1059.
Turvey, C.G., Kong, R., 2010. Weather risk and the viability of weather insurance in China's Gansu, Shaanxi, and Henan provinces. China Agr. Econ. Rev. 2 (1), 5–24. https://doi.org/10.1108/17561371011017469.
Vedwan, N., 2006. Culture, climate and the environment: Local knowledge and perception of climate change among apple growers in Northwestern India. J. Ecol. Anthr. 10, 3–18. https://doi.org/10.5038/2162-4593.10.1.1.
Wang, J., Yang, Y., Huang, J., Chen, K.Z., 2015. Information provision, policy support, and farmers' adaptive responses against drought: An empirical study in the North China Plain. Ecol. Model. 318, 275–282. https://doi.org/10.1016/j.ecolmodel.2014.12.013.
Wang, X., Müller, C., Elliot, J., Mueller, N.D., Ciais, P., Jägermeyr, J., Gerber, J., Dumas, P., Wang, C., Yang, H., Li, L., 2021. Global irrigation contribution to wheat and maize yield. Nat. Commun. 12 (1), 1–8. https://doi.org/10.1038/s41467-021-21498-5.
Weber, E.U., 2010. What shapes perceptions of climate change? Wiley Interdiscip. Rev.: Clim. Change 1, 332–342. https://doi.org/10.1002/wcc.41.
Wolf, J., Allice, I., Bell, T., 2013. Values, climate change, and implications for adaptation: Evidence from two communities in Labrador, Canada. Glob. Environ. Chang 23, 548–562. https://doi.org/10.1016/j.gloenvcha.2012.11.007.
Yu, H., Wang, B., Zhang, Y.J., Wang, S., Wei, Y.M., 2013. Public perception of climate change in China: results from the questionnaire survey. Nat. Hazards 69, 459–472. https://doi.org/10.1007/s11069-013-0711-1.
Zhao, Q., Yu, X., Wang, X., Glauben, T., 2014. The impact of parental migration on children's school performance in rural China. China Econ. Rev. 31, 43–54. https://doi.org/10.1016/j.chieco.2014.07.013.