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The Impact of Climate Change on Maize Yield and Farmers' Adaptation Options: Evidence from Three Provinces of China

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Abstract This paper tries to answer the question that whether farmers can adjust better to climate change in the short-term than in long-term by using panel data models and long difference models respectively. We find that short term weather shocks are less detrimental to maize yield than the long-term climate changes, which can be seen as the evidences of adaptations. For adaptation options, we find farmers choose to decrease maize planting area or enlarge the irrigation inputs to cope with the increase of extreme heat days; when there are more precipitations, farmers will increase the input of fertilizer or labor.

Key words Maize yield, Climate change, Adaptation, China

1 Introduction

Maize is considered to be the most versatile among all crops. It is used for human consumption, animal feed and processing industry. In China, maize demand is sharply growing with the dietary changes and higher meat consumption, which drives China to become a net maize importer at the first time in 2010, and the total maize import values in 2012 reached 1.68 billion dollars (USDA, 2014). Many researchers forecast that future import of maize will continuously increase based on the huge demand, however when taking into account the "95% self -sufficiency policy" in China, the future trend would be still fuzzy. In this case, concerns have been raised about the ability to maintain rates of yield increase in the face of climate change (Lobell and Hammer *et al.*, 2013). Maize is more susceptible to climate change compared to other crops (sorghum, millet, groundnut, and cassava) (Schlenker and Lobell, 2010). Climate change impacts are often characterized by large uncertainties that reflect ignorance of many physical, biological, and socio-economic processes, and it also hampers efforts to anticipate and adapt to climate change. Understanding the impact of climate change on China's maize yield and farmers' adaptation option can stabilize maize yield (Smit and Cai, 1996) and reduce the loss and adaptation cost caused by climate changes effects.

2 Literature review

A large number of studies have investigated impacts of climate change on maize yield (Blanc, 2012), and they mainly focus on the impacts of temperature (extreme temperature), precipitation, drought and transpiration. The majority of studies show negative correlations between yield and temperature; the research of Lobell and Hammer *et al.* (2013) find the main culprit for this negative association is the sensitivity of maize to extreme heat (defined here as accumulation of degree days above 30℃). Lobell and Hammer *et al.* (2013), Tao and Yokozawa *et al.* (2008) find that most major maize producers, including the United States, China, Brazil and Africa, are harmed by warming, especially countries with the highest average yields and well-fertilized modern seed are more susceptible to heat-related losses (Schlenker and Lobell, 2010), as well as drought regions (Lobell and Banziger *et al.*, 2011). Lobell and Field (2007) even find that warming since 1981 has resulted in annual combined losses of three crops (wheat, maize and barley) representing roughly 40 Mt or $5 billion per year from global average yield aspect, and Lobell and Banziger *et al.* (2011) find that roughly 65% of present maize-growing areas in Africa would experience yield losses for 1℃ of warming under optimal rain-fed management, with 100% of areas harmed by warming under drought conditions. The main mechanism of heat damage lies in reducing soil moisture and increasing the severity of drought (Lobell and Burke, 2008). However, not all the high temperatures cause yield loss. For optimal management at present, maize growing below 23℃ in average growing-season temperature tends to gain from warming, especially at relatively cool sites (Lobell and Banziger *et al.*, 2011). Precipitation is generally found to have a positive impact on crop yields (Blanc, 2012), and it is also important contribution to year-to-year variability in crop yields (Lobell and Burke, 2008). Historically, many of the biggest shortfalls in crop production have resulted from droughts caused by anomalously low precipitation (Kumar and Kumar *et al.*, 2004). When dividing regions into less favorable agricultural conditions (LFAC) and more favourable agricultural conditions (non-LFAC), precipitation changes are found to have a larger impact on yields in LFAC countries (Blanc, 2012). However, precipitation are less sensitive than temperature in driving yield response to climate change (Lobell and Burke, 2008; Lobell and Burke, 2010). In some papers, transpiration (vapor) is also considered owing to association between extreme heat and plant water stress,

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which indicates that high vapor pressure deficit (VPD) drives faster transpiration rates (Lobell and Hammer *et al.*, 2013). When reviewing all the available literature, we find fewer papers concentrate on China and use the precise weather variables to measure climate change impacts, and one possible reason might be the complexity and the inaccessibility of the weather data in China. In this paper, we will investigate the long term and short term climate change impacts on maize yield in China using the household level micro-data and the station level weather data.

3 Conceptual Framework and Estimation Methods

To investigate the impacts of climate change and farmers' adaptation induced by climate change, six climate change variables are used by referring to the existed literature. These variables are listed in Table 1.

Table 1 Climate change variables notation and description

Notations	Description
Tem	The average temperatures in the growing period
Spre	The accumulative daily precipitation in the growing period
DDM	Moderate degree days between 8 – 32[2,3]: $dd8\_32_{h,v}=\begin{cases}0 if\ t_{h,v}\leqslant 8\\ t_{h,v}-8 if\ 8\leqslant t_{h,v}\leqslant 32\\ 24 if\ t_{h,v}\geqslant 32\end{cases}$; $DDM_{h,v}=\Sigma dd8\_32_{h,v}$
EDDH	Extreme heat days above 32: $dd32_{h,v}=\begin{cases}0 if\ t_{h,v}\leqslant 32\\ t_{i,r}-32 if t_{h,v}>32\end{cases}$; $DD32_{h,v}=\Sigma dd32_{h,v}$
EDDC	Extreme heat days below 8: $dd8_{h,v}=\begin{cases}8-t_{i,r}\ if t_{h,v}\leqslant 8\\ 0 if\ t_{h,v}>8\end{cases}$; $DD8_{h,t}=\Sigma dd8_{h,v}$

Note: 1. $t_{h,v}$ means the daily temperature of household h in village v; 2. Schlenker, Hanemann, and Fisher 2006 (SHF) argue that degree days between 8 ℃ and 32 ℃ are beneficial whereas temperatures outside this band are harmful.

Panel data model and long difference models are used to evaluate the short-term and long-term weather impacts respectively. The long differences approach allows us to quantify the extent of recent climate adaptation in agriculture (Dell *et al*, 2012, Lobell *et al*, 2011, Dell, Jones, *et al*, 2013). We compare the estimates of climate response of panel model, which estimates the short-term climate response that farms can undertake, with the long differences approach, which captures the long-term adaptations that farmer can undertake. By comparing these two approaches, we will answer the core question that whether the farmers can adjust better in the long-term than in short-term to climate change, which would be interpreted as the evidence of adaptation. Furthermore, we will also consider the adaptation options, such as switching to different seed varieties or applying more irrigation water to a particular crop. Two model formats would be used to estimate the effect of climate change on yield.

$$\log(Y)_{hvt}=\beta_1 X_{hvt}+\gamma_1 Z_{hvt}+V_h+V_t+\varepsilon_{hvt} \quad (1)$$

$$\Delta\log(Y)_{hv}=\beta_2\Delta X_{hv}+\gamma_2\Delta Z_{hv}+\Delta\varepsilon_{hv} \quad (2)$$

where $\log(Y)$ is the logarithm form of yield; $\Delta\log(Y)$ is the first difference between 2010 and 2004 of logarithm yield; X_{hvt} is the vector of climate change variables listed in Table 1, and usually we do not include all the variables in the model at the same time due to the high correlation between certain variables (Massetti, 2013), for example, in this paper the correlation coefficient of tem and DDM is 0.58, which denotes a highly correlation; Z_{hvt} is the vector of control variables, we add different types control variables to test the robustness of the climate change variable coefficients; β and γ are the coefficients vectors of climate change and control variables separately; V_h, V_t are household fixed effect and time-variant fixed effect separately. Model (1) is the panel data model, and it will be used to estimate the short-term response to climate change. Model (2) is the long differences model with the difference over two periods (2010 and 2004) at the household levels.

4 Data and statistical description

The yield data and other social character data were mainly collected from rural fixed watch points of the Ministry of Agriculture in three provinces from 2004 to 2010, and 2337 households were included per year and they were located in 38 villages among 3 provinces. These three provinces are Heibei, Shandong and Henan. They are all located in Yellow-Huai River Valley maize belt. The predominant maize system is irrigated summer maize either rotated or relay-cropped with winter wheat in the plain areas. Other major crops in this system include cotton, peanuts, and vegetables. The summer maize cycle averages 110 – 115 days. The type of maize, the seeding and harvest time and the possible extreme weather are illustrated in Table 2.

Table 2 Maize growing periods and the extreme weather

Province	Type of maize	Seeding time	Harvest time	Extreme weather
Hebei	Spring maize	Middle third of June	last third of September	Extreme heat
Shandong	Summer maize	First third of June	last third of September	Extreme heat
Henan	Summer maize	First third of June	last third of September	Extreme heat

The climate change daily data are acquired from China Meteorological Bureau and The Weather Channel Companies. The weather stations selected in this paper are Personal Weather Stations (PWS's), which are part of Weather Underground's ever-expanding PWS network, and these stations implement strict quality control and observations are updated as often as every 2.5 seconds. Table 3 is the statistical description of climate change variables, maize planting area and yield.

5 Emperical results

Two specific models are used to estimate the short term effects of climate change on yield; in equations (3) we use temperature to measure degree days, but in equations (4) the temperature is replaced by DDM:

$$\log(Y)_{hvt} = \beta_1 spre_{hvt} + \beta_3 tem_{hvt} + \beta_5 EHD_{hvt} + \gamma_1 Z_{hvt} + V_h + V_t + \varepsilon_{hvt} \quad (3)$$

$$\log(Y)_{hvt} = \beta_1 spre_{hvt} + \beta_3 DDM_{hvt} + \beta_5 EHD_{hvt} + \gamma_1 Z_{hvt} + V_h + V_t + \varepsilon_{hvt} \quad (4)$$

where Z_{hvt} is vector of control variables, which includes inputs, village-specific time trend. The control variables are crucial to testifying the robustness of climate change variable coefficients. When employing Hausman test in these two models above, we find they all reject the null hypothesis, which means that we should choose fixed effect panel data model rather than random effect model.

Table 3 Statistical description of variables

Variables	Notations	Mean	SD	Min	Max
Maize Yield per hectare	Y	6313.6	1682.3	0.0	22498.9
Maize plant area per household (ha)	mar	0.2	0.2	0.0	1.3
Maize production per household (kg)	mp	1471.7	1137.6	0.0	10880.0
Average temperature (℃)	tem	24.7	1.3	18.6	26.6
Aggregate of precipitation in growing period (mm)	spre	354.1	122.6	129.1	926.4
DDM between 8&31 (℃)	DDM	2057.9	285.2	1277.0	4184.0
Extreme heat days above 31 (℃)	EHD	2.7	4.3	0.0	22.0

5.1 The estimate results for panel data model

In Table 4, we estimate six models which are distinguished by village-specific time trend or input variables. When comparing the results among different models, we find the coefficients of "extreme heat days" and precipitation are relatively constant, which denotes the robustness of the estimation results. Extreme heat weather has significantly negative effects on yield, and precipitation has positive effects on yield, which is identified by Tianyi Zhang *et al* (2011). An increase of 1 ℃ in extreme heat days would decrease maize yield by 0.2% in the short term, and 10mm increase in precipitation will increase maize yield by about 1%.

Table 4 Estimate results of panel data model

Log(yield)	Model (1) Variables	Model (2) Log(yield)	Model (3) Log(yield)	Model (4) Log(yield)	Model (5) Log (yield)	Model (6) Log(yield)
Precipitation in Grow. Per	0.005**	0.013*	0.011**	0.001	0.001	0.015***
(100mm)	(0.001)	(0.007)	(0.005)	(0.005)	(0.00026)	(0.002)
Average temperature (℃)			-0.00603		-0.00116	
			(0.00603)		(0.01063)	
DDM between 8&31 (℃)	0.00009	0.00023		0.00009		0.00036
	(0.0002)	(0.0001)		(0.0003)		(0.00023)
Extreme heat days above 31 (℃)	-0.00213*	-0.00309***	-0.00308***	-0.00292**	-0.00289**	-0.00391***
	(0.00113)	(0.00096)	(0.00092)	(0.00138)	(0.00145)	(0.00113)
Constant	6.12769***	5.69245***	5.82485***	5.59916***	5.69877***	5.20581***
	(0.29938)	(0.21008)	(0.15622)	(0.44583)	(0.31309)	(0.34148)
Input variables	N	N	N	Y	Y	Y
Village - specific time trend	N	Y	Y	N	N	Y
Time fixed effect	Y	Y	Y	Y	Y	Y
Observations	16,078	16,078	16,078	12,232	12,232	12,232
Number of groups	2,297	2,297	2,297	1,947	1,947	1,947

Note: (1) Standard errors in parentheses (2); *** $p<0.01$, ** $p<0.05$, * $p<0.1$; (3) Control Variables include the total material fee and labor input.

5.2 The estimate results of the long term difference model

In this section, we differentiate the variables between the year 2010 and 2004 to check the long term climate effects on yield (Mashell, 2013), and the dataset turns to be cross-sectional data. As stated in other papers, the endogenous explanatory variables in multiple regressions problem would appear owing to the missspecication errors, measurements errors, and most commonly omitted variables. In this case, the Instrumental Variables (IV) is an effective tool to solve the problem of endogenity, and the estimation method which fits the instrumental variables is Two Stage Least Squares (2SLS). In general, the qualified instrument variables satisfy two requirements: one is that instrument variable should be highly related to the being-instrumented variables; the other is that the instrument variable should be not in relation with residuals. Based on these criteria, we choose two instrument variables: "average temperature of non-growing period" (ntem) and "average precipitation of non-growing period" (npre). These two variables are highly related to EHD variable, but not related to maize yield. In Table 5, we present the correlation coefficients of lmy, EHD, npre and ntem, which literally prove the validity of the selected instrument variables.

Table 5 Correlation coefficients of variables

	LD [Log(Y)]	LD(EHD)	LD(ntem)	LD(npre)
LD [Log(Y)]	1			
LD(EHD)	-0.0195	1		
LD(ntem)	0.0257	0.214	1	
LD(npre)	-0.0347	0.1857	-0.5673	1

Table 6 presents the results of IV estimation and OLS estimations to prove the necessity of IV estimation, and we perform Hausman test by comparing the coefficient of model 1 with that of model 3 and model 2, respectively. The results show that model 1 with 2SLS estimation is better than model 3 owing to the endogenity problem.

Table 6 Results of LD cross-sectional IV estimation and OLS estimation

	(1)	(2)	(3)	(4)
	IV	IV	OLS	OLS
VARIABLES	LD[log(yield)]	LD[log(yield)]	LD[log(yield)]	LD[log(yield)]
LD(precipitation)	0.051***	0.004	0.006	-0.007
	(0.010)	(0.007)	(0.006)	(0.005)
LD(temperature)		-0.08337***		-0.07323***
		(0.01649)		(0.01082)
LD(DDM)	-0.00048***		-0.00024***	
	(0.0001)		(0.00006)	
LD(EHD)	-0.00790*	-0.01308***	-0.00163	-0.00048
	(0.00418)	(0.00305)	(0.00152)	(0.00151)
Constant	0.21076***	0.25989***	0.09454***	0.11051***
	(0.05328)	(0.03990)	(0.01282)	(0.01285)
Observations	1,803	1,803	2,297	2,297
R-squared	0.13426	0.12310	0.09043	0.10300

Note: '***', '**', '*' stand for the significance at 1%, 5%, 10% level separately; standard errors in parentheses (b - V_B)^(-1)(b - B); Ho means that difference in coefficients is not systematic.

To theoretically test the vaildity of instrument varibles, we perform sargan test on model 1 and model 2. The value of $N*R^2$ is 0.14 and 23.09, and possiblity rate is 0.705 and 0.000001 seperately, which means that "average temperature of non-growing period" (ntem) and "average precipitation of non-growing period" (npre) are valid instrument variables in model 1, but not valid in model 2. By comparing the the extreme heat days (EHD) coefficients, we find that long-term extreme heat days (EHD) have more severely negative effect on yield than short-term EHD. The reason is that farmers can adjust their farming strategies in the short-term when extreme weather happens to reduce their cost (Mashell *et al* 2013). In the following section, we analyze the possible adaptation options farmers may choose when facing extreme weather.

5.3 Adaptation options Panel model specifications are used to evaluate farmers input options in terms of climate changes. From model 1 to model 6, we all control the village and time fixed effects. In general, farmers change their input options by referring to last period's weather situations, so we use the lag of weather variables as independent variable. The results in Table 7 show that with the increase of extreme heat days, farmers are reluctant to plant maize or enlarge the irrigation inputs. With the increase of precipitation, farmers will increase the input of fertilizer or labor.

Table 7 The adaptation resources

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	seed	fertilizer	labor	irrigation	machinery	area
L1. DDM	-0.00013**	-0.00022***	0.00025***	0.00006	-0.00009*	0.00005
	(0.00006)	(0.00006)	(0.00006)	(0.00008)	(0.00005)	(0.00003)
L1. spre	0.00005	0.00021***	0.00021**	-0.00001	0.00022	0.00020
	(0.00004)	(0.00005)	(0.00010)	(0.00009)	(0.00015)	(0.00013)
L1. EHD	0.00064	-0.00646***	0.00138	0.00636**	-0.00363	-0.00528***
	(0.00078)	(0.00133)	(0.00140)	(0.00271)	(0.00249)	(0.00122)
Constant	3.65581***	4.72175***	1.93851***	1.67993***	3.05713***	0.00000
	(0.12009)	(0.13635)	(0.13018)	(0.14581)	(0.08808)	(0.00000)
Observations	14022	14022	10,418	14,022	14,022	10,496
Number of groups	2337	2337	1,936	2,337	2,337	1,953

Note: L1. means one period lags; '***', '**', '*' stand for the significance at 1%, 5%, 10% level separately; standard errors in parentheses.

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team, recruit a good many young people graduated from agricultural colleges and universities, expand the agricultural technology extension service system team, gradually realize work-with-post system, and improve overall quality of the agricultural technology extension service team.

4.3 Taking protective measures for grass-roots agricultural technology extension workers Services of agricultural technology extension departments are free, apart from basic wage, agricultural technology extension departments have no other economic return, thus only effective protection can help them bring into full play their public welfare function. Firstly, it is recommended to formulate detailed local regulations on protecting agricultural technology extension services on the basis of new *Agricultural Technology Extension Law*, safeguard effective implementation of agricultural technology extension services, and reinforce agricultural law enforcement. Secondly, it is recommended to strengthen infrastructure construction for grass-roots agricultural technology extension system, gradually provide necessary service facilities, improve technological equipment level for serving modern agriculture, and gradually improve conditions of grass-roots agricultural technology extension system. Thirdly, it is recommended to increase financial support, take effective safeguard measures, and ensure financial input and gradual increase of funds for agricultural technology extension. Apart from basic wages, it is required to increase input in office funds, facility funds, and education and training funds, to prevent agricultural technology extension activities from influence of lack of funds.

4.4 Improving evaluation mechanism and stimulating enthusiasm of agricultural technology extension workers Government organs should strengthen supervision and evaluation of duty performance of agricultural technology extension organizations, warn those unacceptable organizations, and no longer hire those agricultural technicians not qualified for two consecutive years, and provide award for excellent technicians. Evaluation results should connect with distribution of bonus, employment of technicians and promotion of post, so as to stimulate working enthusiasm of grass-roots agricultural technology extension workers and make them better work for agricultural technology extension services.

5 Conclusions

After the implementation of new *Agricultural Technology Extension Law*, the agricultural technology extension service of Hanjiang District will have better development opportunity and face greater challenges. Thus, Hanjiang District should grasp this opportunity and get ready for challenges. The agricultural technology extension workers should bring into play their working enthusiasm, and devote to agricultural technology extension service system, to make contribution to modern agricultural development of Hanjiang District.

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6 Conclusions

In this paper, we use panel data models and long difference (2010 to 2004) models to estimate the short-term and long-term climate changes on maize yield separately; we find that long-run extreme heat days have more severe negative effect on yield than short-term extreme heat days. An increase of 1 ℃ on extreme heat days will decrease 0.2% yield in the short-term and decrease 0.7% yield in the long term, it is mostly because farmers can adjust their planting strategy (such as fertilizer, irrigation, labor inputs) more flexibly in the short term than in the long term. As for the adaptation options, we find that with the increase of extreme heat days, farmers are reluctant to plant maize or enlarge the irrigation inputs. With the increase of precipitation, farmers will increase the input of fertilizer or labor to improve the maize yield.

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