Climate Change, Risk and Grain Production in China[Ψ]

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Abstract:

This paper employs the production function-based method proposed by Just and Pope (1978, 1979) to explicitly analyze production risk in the context of Chinese grain farming and climate change, and test for a potential endogeneity of climate factors in Chinese grain production.

Our results indicate that China might, at least in the short run, become a net beneficiary of climate change. In particular, we find that increases in annual average temperature increase mean output at the margin and at the same time lead to a reduction of production risk. Further calculations suggest that a 1 °C increase in annual average temperature would entail an economic benefit of $1.1 billion due to the increasing mean output. Furthermore, a Hausman test reveals no endogeneity of climate variables in Chinese grain production.

Keywords: Agriculture, grain production, climate change, production risk, China

JEL Classification: Q1, Q54

1 Introduction

Farmers usually have no knowledge of the precise output when they make their production and input decisions, which is mainly due to the fact that agriculture in general has a long production cycle and is affected by a large number of endogenous or exogenous uncertainty factors. The prevailing climatic conditions for instance are important sources of uncertainty. Factors such as temperature, precipitation or sunshine however are characterized by inter-annual variability, part of which can be explained by gradual shifts in mean conditions but another part is constituted by seemingly random fluctuations. The overall direction and magnitude of the inter-annual variations are beyond farmers' control and their predictive capabilities as well. As a result, climate is not only an important determinant of the general suitability of any given region for agricultural production but also a source of substantial production risk, causing unexpected variability of output.

In addition to climate-related risks, Just and Pope (1979) as well as Kumbhakar and Tsionas (2008) argue that the level of risk is also endogenously determined by the applied quantities of standard physical inputs, such as fertilizers and pesticides. Therefore, it is quite complicated to conduct risk analyses with respect to agricultural production.

Even though risk analysis is a very important topic for agricultural production in China both from a policy and an academic perspective, most scholars so far have not paid appropriate attention to the risk aspect, in particular not to climate-related risks, and only focus on the deterministic contributions of inputs, such as land, labor, fertilizer, machinery and irrigation to output creation. Yu and Zhao (2009) provide a good review of the existing studies on agricultural production in China. However, with the exception of Zhang and Carter (1997) and Mendelsohn (2009), most studies have not explicitly

considered climate factors in their analyses of the state and prospects of Chinese agriculture. Specifically, Zhang and Carter (1997) take climate variables as normal inputs in production, whereas Mendelsohn (2009) studies the impacts of climate variables on farmers' net revenues. However, the issue of production risk stemming from climate factors and standard physical inputs as well as farmers' possibilities to adapt to this risk have, to our knowledge, not been well addressed in the present context.

The world climate is changing (Shortle et al., 2009; Parry et al., 2007), the consequences of which are and will be very significant. However, the studies on the impacts of climate change on agricultural production produce a multitude of different results. For instance, some studies find that an increase in temperature could benefit agricultural production in some developed countries, such as the US (Mendelsohn and Dinar, 2003; Deschênes and Greenstone, 2007; Shortle et al., 2009) and Germany (Lippert et al., 2009), while others conclude that global warming can harm agricultural production in some developing countries in Africa and South America as well as in China (Mendelsohn, 2009; Féres et al., 2008). In addition, Schlenker and Roberts (2006, 2009) indicate that the relation between temperature and corn yields is nonlinear: The impacts of increases in temperature on yields are positive in moderate temperature ranges, but quickly turn negative once temperatures exceed 30°C.

As shown in Figures 1 to 3, China is no exception to this trend and its grain production to a considerable extent depends on the development of the regional and the global climate. As a result of the country's exposure to the East Asian monsoon, its climate and particularly precipitation patterns are already characterized by a high degree of variability (Tao et al., 2004), which frequently leads to floods or droughts (Smit and

Yunlong, 1996). It is generally expected that climatic variability in terms of such extreme weather events will increase in the foreseeable future. In addition, mean climate conditions are also forecasted to change. On the one hand, following a gradual warming over the past five decades, East Asia is expected to experience a substantial increase in annual average temperatures until 2100 and on the other hand, some climate simulations also forecast an increase in total annual precipitation levels during that time period (Christensen et al., 2007). The latter could counteract the trend towards less precipitation observed over the past 50 years (Song et al., 2005).

These changes will likely have profound impacts on Chinese agriculture in terms of both expected output and production risk. For instance, Mendelsohn (2009) shows that global warming slightly reduces farmers' revenues in China. Historical evidences have also shown that variations of agricultural production in China have increased the volatility of world food prices (von Braun et al., 2007) because a bad harvest year in China could drive the country to import more food, which in turn pushes up the world market price. Hence, the study of the impacts of climate change on agricultural production in China may hold important policy implications even beyond China.

On the other hand, scientific evidences have shown that agricultural production may impact climate through landscape changes, the application of chemical inputs, the use fuel and electric energy and through carbon sequestration (Desjardins et al., 2007). Greenhouse gases (GHGs) represent one of the driving forces of climate change and two of the major emission sources in agriculture are the large-scale application of synthetic nitrogen fertilizer, which particularly leads to the release of nitrous oxide into the atmosphere (Eickhout et al., 2006), and the increasing energy use which is responsible for

the emission of large amounts of CO_2. Since the first half of the 1990s, China is the world's largest consumer of chemical fertilizer and ranks among the major producers. The national average quantity of fertilizer applied per hectare of farm land was nearly three times the world average in 1992 (Wang et al., 1996, Yu and Zhao 2009). Another important GHG emitted in the course of agricultural production is methane, which is a byproduct of rice cultivation on flooded fields and of the digestive process of animals (Smith et al., 2007). The former of course is particularly relevant with respect to grain cultivation in China. In addition, forestry and agriculture are important tools for climate change mitigation. For instance, they are important carbon sinks. However, landscape change, in particular deforestation for the purpose of expanding agricultural land and the transformation of agricultural to non-agricultural land due to urbanization, decrease the potential carbon sequestration and could therefore contribute to changes in the regional and global climate. The above considerations would imply that climate factors might be endogenous variables in agricultural production. In the current literature on the impact of climate factors on agricultural production in China, such as in Zhang and Carter (1997), this aspect has however not been tested for. If the climate variables are endogenous, the estimation results in current literature would be inconsistent.

Hence, following the above considerations, the main objectives of this paper are (1) to analyze how climate change and the related risks affect grain production in China and (2) to test whether climate change is indeed endogenous given the possible feedback between agriculture and climate. We use a data set for a panel of 26 Chinese provinces comprising variables relevant for grain production and climate information from 1985

through 2007, which is a time period that is long enough to observe changes in climatic conditions.

2 Models and Estimation Approaches

2.1 Background of models

In the current literature, either the production function or the Ricardian approach is used to estimate the economic impacts of climate change. The Ricardian approach including climate factors and other exogenous variables as regressors, which aims at analyzing the determinants of the productivity of farmland, is particularly prevalent because less data are required. The variables representing productivity of farmland in the current literature include land rent (Lippert et al., 2009), land value (Féres et al., 2008), and net revenue (Mendelsohn et al., 2003; Mendelsohn, 2009) and profit (Deschênes and Greenstone, 2007) per unit of land. However, there are some unobserved heterogeneities in error terms when using the Ricardian method, such as some inputs (e.g. fertilizers) or soil quality (Deschênes and Greenstone, 2007), which can be correlated with climate variables. It hence causes endogeneity problems in regressions and the estimation results might be inconsistent.

Furthermore, the agricultural land in China is equally distributed to farmers and there is no open market for farmland, so that neither rents nor values of farmland can be observed in China. Hence, we decide to use the production function approach. While Deschênes and Greenstone (2007) indicate that farmers' adaptations to climate change are constrained in the production function approach, which may bias the estimates with respect to climate change, this approach has the benefit that we can use it to study the

impacts of climate-related risks on agricultural production in China. This is particularly important because the issue of risk has not been well studied in the current literature on agricultural production and climate change in China.

In addition, the borders between Ricardian approaches and production function approaches are not clear-cut. Broadly speaking, the Ricardian methods proposed by Mendelsohn et al. (2003), Mendelsohn (2009) and Deschênes and Greenstone (2007), which use net revenues or profits per unit of land as measures of productivity, can be considered a special case of the production function approach. Furthermore, in our real world, farmers cannot predict the weather conditions for the whole cropping season at the stage of planting, so that the production costs might not be a function of weather conditions. In that case, the model of Deschênes and Greenstone (2007) would just degenerate to the model of Mendelsohn et al. (2003) and Mendelsohn (2009):

(1) $$V = f(x) \ ,$$

where V is the net revenue per unit of land and x is a vector of exogenous variables, including climate variables, which determines the net revenues or, more generally, the land productivity. If we would include the input variables as independent variables in equation (1), it would exactly be production function with constant returns to scale.

2.2 Base Model

In this study, we employ a Cobb-Douglas production function because this specification has been found to be a reasonable empirical approximation of production processes in many parts of the economy, including agriculture, and has thus frequently been used for research on agricultural production (e.g. Hayami, 1969; Dawson and Lingard, 1982;

Echevarria, 1998; Hu and McAleer, 2005; Armagan and Ozden 2007). The basic model is thus specified as:

$$(2) \quad \ln y_{it} = \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_{kit} \ ,$$

where y_{it} is the grain output in region i at time t; x_{kit} is the input quantity of factor k in region i at time t, and α_j, $j = 0,1,\cdots,K$, are the parameters to be estimated.

As the production function is specified in a log-linear way, the coefficient estimates for α_j on this stage will be elasticities of output with respect to the respective input factors.

First, we estimate aggregate Chinese grain production, considering only a set of standard physical inputs, which includes the land area under cultivation, the irrigated area, labor, fertilizer as well as the use of machinery.

However, as aforementioned, production risks are doubtlessly present in most parts of agricultural production. They can be assumed to take the form of heteroskedasticity in the production function (Just and Pope, 1979). Consequently, a fixed effects estimator, which would usually be appropriate if the sample consists of large and heterogeneous geographical entities like the Chinese provinces, would yield inefficient though still consistent coefficient estimates. If additionally a first-order autoregressive process is present in the error terms, this will cause further inefficiency with respect to the estimates of an FE regression (Wooldridge, 2002). In order to remedy both issues on this first stage of the analysis, a feasible generalized lest squares estimator (FGLS) will be employed instead (Wooldridge, 2002).

On the second stage, we acknowledge the conjecture that the model used so far might not be correctly specified since it does not include climate variables, which are however of critical importance regarding the output of grain. Following Zhang and Carter (1997), we consequently proceed by estimating a weather and input production function that includes both the first and second central moments of temperature, precipitation and sunshine in the same way as regular input factors. Given the issues of heteroskedasticity as a result of inherent production risk and serial correlation, we might again resort to an FGLS approach.

2.3 Endogeneity

Note however, that an important precondition for the consistency of an FGLS estimator is that all independent variables are strictly exogenous. While it will be assumed for the moment that this condition is satisfied, it cannot be ruled out at this point that the included climate variables are endogenous as a result of the possible feedback influences of agricultural production on climate change mentioned above. We are concerned about the endogeneity of climate variables both from an econometric and from a policy perspective. If climate variables are endogenous, the estimation results would not be consistent. Furthermore, agricultural policies should in that case take the feedback effects of agriculture on climate into account.

A Hausman test (Hausman, 1978) is being employed to test for potential endogeneity of the climate variables in our model. It determines whether the estimation results of a fixed effects estimator are significantly different from those obtained using an

instrumental-variable (IV) estimator[1]. If the null hypothesis of there being no difference between the estimators is rejected, the IV estimator would be preferred; otherwise, the estimator of the fixed-effects model is preferred.

2.4 Risk Analysis

Just and Pope (1978, 1979) suggest that production risks can take the form of heteroscedasticity in the production function. Following them, we develop a non-linear fixed-effect panel data model to separately analyze each input factor's marginal contribution (considering both standard and climate inputs) to the mean of output as well as to production risk. Based on Just and Pope's generalized production function, our model is specified as follows:

$$(3)\quad y_{it} = \exp(\alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_{kit}) + \varepsilon_{it} \sqrt{\beta_0 + \sum_{m=1}^{M} \beta_m \ln x_{mit}} \ ,$$

where y_{it}, x_{kit} and α_k have the same definition as in equation (1); x_{mit} denotes a factor which can influence the risk level and β_m is the corresponding coefficient. ε_{it} in turn is a stochastic disturbance term following the standard normal distribution.

Thus, we find that the expected output (often also referred to as mean output) and the variance of output are determined by separate functions, which can algebraically be denoted as $E(y_{it}) = \exp(\alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_{kit})$ and $V(y_{it}) = \beta_0 + \sum_{m=1}^{M} \beta_m \ln x_{mit}$ respectively. Drawing on the above assumption that production risk in this framework takes the form of heteroskedasticity in the production function, the second term on the right-hand side of

[1] We use one-year and two-year lags as instruments respectively.

equation (2) can also be interpreted as a heteroskedastic error term for the purpose of estimation.

Just and Pope (1979) proposed a three-step method for estimating the non-linear Just-pope model, which will be applied with some modifications for panel-data models in estimating equation (2): (1) Estimation of the mean output function with fixed effects[2], (2) estimation of the risk function with fixed effects model; and (3) re-estimation the mean output function with the method of generalized non-linear OLS.

2.5 Impact Analysis

Another important issue is to calculate the costs or benefits of climate change because it has very important policy implications, which is underlined by the fact that many current studies are concerned with this question. From our production function (equation 3) we can calculate the shadow prices of climate variables as follows:

$$(4) \qquad w_c = \frac{\partial E(y)}{\partial c} p_y$$

$$= \alpha_c \frac{p_y * E(y)}{c},$$

where w_c is the shadow price of climate variable c (e.g. annual average temperatures), E(y) is the expected output and p_y is the output price. α_c in turn represents the estimated output elasticity with respect to the climate factor c, which in our case is obtained from the mean production function of the Just-Pope procedure. This equation thus quantifies the economic impacts of a marginal change in climate.

[2] The fixed-effects panel model is estimated using the method of non-linear OLS with a dummy variable for each province.

3 Data

A data set for a panel of 26 Chinese provinces comprising variables relevant for grain production and climate information from 1985 through 2007 is used to carry out the analyses in this paper. The main variables regarding grain production include yearly observations of grain output, cultivation area, labor, irrigated area, machinery use as well as chemical and energy inputs, while the data on climate consist of monthly observations with respect to temperature, precipitation and sunshine. The data set is constructed from various issues of the China Statistical Yearbook (National Bureau of Statistics of China, 1986-2008).

Except for the land area under cultivation, the available input data generally represent aggregate input use regarding all subsectors of a province's agricultural production. In order to approximate the province-specific quantities of labor, fertilizer and machine power used for the production of grain, the respective total input quantities have been adjusted using estimated regional-level input shares by Zhang and Fan (2001)[3]. Based on their subdivision of China into seven regions (northeast, north, northwest, central, southwest, south and east) each province's inputs have been adjusted by its region's average input shares with respect to grain production over the period from 1985 until 1996[4]. Following Zhang and Carter (1997), the irrigation input has been

[3] Additional data on input shares were obtained from an earlier working paper version (Zhang and Fan, 1999).

[4] Input shares for the years from 1997 until 2007 were not available. Consequently, it was not possible to match the different regions with a unique estimate for each year and elongating Zhang and Fan's (1999) time series by means of extrapolation over the missing eleven years would have created unreasonably low input shares in some regions. Therefore, the use of the average shares over the first twelve years of this study (1985-1996) for the entire sample period was opted for. Of course, this together with the fact that the

adjusted so as to represent only the area of irrigation used in the course of grain production by multiplying it with the percentage share of grain production in total agricultural area, which entails the simplifying assumption of equal intensities of irrigation for all crops.

For each of the above climate factors, we construct variables representing their first and second central moments. First moments are the annual averages of temperature and duration of sunshine as well as total annual precipitation. With respect to the second moment variables, we first calculate the deviation of each of the monthly observations regarding each climate factor (temperature, precipitation and sunshine) from the respective month's linear growth trend over the period from 1985 through 2007. Next, we sum up the deviations of each climate factor within any given year and use these sums as proxies for the variability of climate that farmers cannot predict when they make their input decisions.

4 Estimation Results and Discussion

- Model Comparison

The regression results of the above multi-stage analysis are presented in Table 1, which includes 4 econometric models: Model I is a standard fixed-effects panel model without inclusion of climate variables; Model II uses Feasible GLS estimation for the fixed-effects model without climate variables, which is an improvement over Model 1 because testing shows that the error terms in Model I are serially correlated; Model III yields the Feasible GLS estimator for the fixed-effects model including climate variables;

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estimated input shares already entail some degree of uncertainty underlines the approximative nature of the adjustment.

and Model IV is the estimation results of the fixed-effects Just-Pope model with a mean production function and a risk function.

In particular, comparing the results of the mean production functions in Model III and Model IV, we find that the coefficients of cropping area, fertilizer, machinery, average temperature and temperature deviation are statistically significant in both models, and those for labor, precipitation deviation, and the deviation of sunshine duration are not significant in either model. However, the coefficients for irrigation, total precipitation and average sunshine duration are statistically significant in Model III but not in Model IV.

As we know, the Just-Pope model is superior to the other approaches because it explicitly captures risks in production, which play crucial roles in agriculture. The coefficients in the other models, which do not include risk factors, may mix up the contributions to mean output and to production risk. Hence, the following discussion will be based on the Just-Pope model.

- Mean Production Function

Regarding the marginal contributions of the standard physical input factors to the mean of output, we find land to be of crucial importance. It features an output elasticity of 0.79 in Model III and 0.995 in the Just-Pope model. Both results are significant at the 1%-level. Compared to land, the magnitude of all other estimated coefficients is rather small. The output elasticity with respect to land of almost 1 can be explained by the fact that land has become the most serious constraint to a further expansion of grain cultivation in China because the possibilities for increasing the acreage are widely exhausted and in some regions, the arable land, in particular the most fertile land, is even

shrinking as a result of increasing urbanization and growing burdens on the environment causing soil degradation and desertification (Smit and Yunlong, 1996).

Fertilizer and Machinery also significantly contribute grain production in China, though the marginal effects are not very large. The estimation results of the Just-Pope model show that the output elasticity with respect to fertilizer is 0.13 and statistically significant at 1% level. As aforementioned, China features one of the most fertilizer-intensive agricultural sectors in the world. Nevertheless, the small marginal contribution of fertilizer obtained here is still positive. The output elasticity with respect to machinery is 0.07 and also statistically significant at the 1% level. In China, the land is equally distributed among farmers and each farmer operates on small and often fragmented plots of land. Consequently, large-scale machinery can often not be used, which in turn causes small-scale machinery to be much more prevalent. As a result, the marginal effects of machinery are unsurprisingly small but still significant.

However, an increment in agricultural labor ceases to have a significant impact on marginal output after climate factors have been considered. This result seems to be in accord with the finding of Bowlus and Sicular (2003), who conclude that some regions in rural China are characterized by a considerable labor surplus. It thus makes sense that the output elasticity with respect to labor is not statistically significant and that the point estimate is only 0.014, which is very small. We also do not find consistently significant results for the area under irrigation. This might be the result of an increasingly unreliable and scarce supply of water for irrigation purposes related to an ongoing depletion of water resources, especially in Northern China, and climatic changes affecting

precipitation and more generally moisture levels, so that there might not be enough water for irrigation purposes (Smit and Yunlong, 1996).

Turning now to the impacts of climate factors on the mean of output, we find a positive and significant output elasticity with respect to the annual average temperature. Given that China is large enough to span a number of different climatic zones ranging from cool temperate climate in the north to tropical climate in the south and desert-like climate in parts of its western half together with the fact that our output variable captures a whole range of different grain crops that respond differently to climatic changes, the impact of an increment in temperature was highly uncertain a priori. In particular, we find the elasticity of output with respect to temperature to be 0.156, which indicates that the benefits from higher annual average temperatures could outweigh the losses on a national scale, which would ceteris paribus make China a net beneficiary of global warming with regions in the cooler northern part of the country being more likely to gain and already warm regions in the south being more likely to be adversely affected. Similar results have for example been found for the USA (Shortle et al., 2009; Deschênes and Greenstone, 2007; Mendelsohn and Dinar, 2003) and Germany (Lippert et al., 2009).

Drawing on the result just described and using equation (4), we can calculate the economic benefit of global warming with respect to Chinese grain production. Given an average temperature of 15.14^{o}C[5] in China's 30 main cities in 2007, a grain output of 501.6 million tons[6] and an average grain price of 1.598 yuan/kg[7], the shadow price of temperature is:

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[5] Source: China Statistical Yearbook 2008, Table 11-13 (National Bureau of Statistics of China, 2008).
[6] Source: China Statistical Yearbook 2008, Table 12-2 (National Bureau of Statistics of China, 2008).

w_T = ¥8.3 billion

≈ $1.1 billion[8],

which implies that the benefit of a global warming of 1 °C accruing to Chinese grain production would have a value of $1.1 billion.

The total annual amount of precipitation and the average duration of sunshine in turn are not consistently significant. While we would have expected that an increase in precipitation should be beneficial for Chinese agriculture, especially given the increasing water scarcity in some regions mentioned before, we assume that our ambiguous results obtained with respect to this climate factor might be caused by other factors impeding a beneficial impact of an increase in precipitation. As a result of China's exposure to the Eastern Monsoon, increases in precipitation are most likely to be observed in the south eastern part of the country, which already features a comparatively high level of water availability, and increases in precipitation that occur during the monsoon season often cause floods and could therefore cause damage to agricultural production in China. Thus, additional precipitation might not necessarily exert a positive marginal influence on the national level.

With respect to our second central moment climate variables, only the variability measure of temperature turns out to be consistently positive and highly significant. At first glance, this result is contrary to common wisdom because strong or frequent positive

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[7] Source: Shandong Development and Reform Commission, http://www.sdjw.gov.cn/show.asp?type=zwgk&id=228

[8] Exchange rate: USD 1 = CNY 7.581127 (2007).

or negative deviations from average temperature, leading to heat waves or frost events, should subject crops to adverse heat stress and thereby reduce mean output. However, it can also be argued that a certain degree of climatic variability within a year can also increase the output of many crops. Particularly winter wheat is known to benefit from such variability as it needs a cold period of limited duration in order to flower properly in spring.

- Risk Function

Our analysis of production risk in Chinese grain farming by means of Just and Pope's procedure reveals that the area under cultivation is the only physical input factor that is associated with a positive and significant risk elasticity. We attribute the risk-decreasing impact of land primarily to the fact that a larger total area under cultivation in any given province should offer better chances of diversifying the output structure even within the comparatively narrow category of grain crops considered in this analysis. This in turn is likely to reduce the share of damaged output in case of localized extreme (weather) events like heat waves, heavy rain or pest infestation because different crops vary in their sensitivity towards such influences.

Climate factors themselves also turn out to significantly affect production risk in Chinese grain farming. The risk elasticity with respect to the annual average temperature in particular has a strongly risk decreasing influence, which can be explained by the development of this climate factor over time. While it has generally been observed that annual average temperatures are increasing, there is also evidence that winter temperatures have increased more strongly than summer temperatures. Thus, we conclude that along with these changes, there should be a negative impact on the severity

and frequency of extreme cold events, which likely decreases the risk of frost damage in agriculture. The potentially adverse impact of an increased summer temperature on production risk is likely to be somewhat less severe because on the one hand the warming of the summer months has been less pronounced and on the other hand especially the colder northern part of China might well benefit not only from higher winter temperatures but also from higher summer temperatures[9]. The associated risks stemming from possible heat waves or water shortages so far seem to be outweighed on the national level by the above-mentioned benefits.

Furthermore, we find a significant risk-decreasing marginal effect of total annual precipitation. Given the issue of water scarcity in China due to an increasing demand from agricultural and non-agricultural sources and also a decreasing supply (partly as a result of changing precipitation patterns and quantities), an increase in total annual precipitation would reduce the risk of output losses from unexpectedly dry conditions by directly providing necessary water to plants and by partially replenishing ground water resources, which are often tapped for irrigation purposes.

- Endogeneity

Finally, for the reasons discussed earlier, we are concerned about the possible endogeneity of climate variables both from an econometric and from a policy perspective. We therefore use one-year and two-year lags of the climate variables as instruments respectively to estimate Equation (1) with climate variables included. Hausman tests

[9] The benefits of higher annual average temperatures, particularly in temperate regions, most importantly include an extended growing season and potentially more favorable growing conditions for a number grain crops that are better adapted to warmer environments.

(1978) however cannot reject the null hypothesis of there being no systematic difference between the fixed-effects model and the two IV regressions. Consequently, the climate variables can be considered to be exogenous factors in Chinese grain production. In the light of this, we conclude that climate change is affecting grain production in China while the feedback effects of agriculture are not significant. Methodologically, the tests ensure that the estimation results of the fixed-effects model and the Just-Pope model are consistent, so that the above discussions are legitimate.

5 Conclusions

This paper has contributed to the current literature in several ways. We have used the most recent data available to determine the marginal contributions of a range of standard physical input factors to the creation of grain output in China. Furthermore, we have used climate data to analyze output elasticities with respect to both first and second central moment variables of temperature, precipitation and sunshine. After that we have used the method developed by Just and Pope (1978, 1979) to determine each input factor's contribution to production risk at the margin. Lastly, we tested for the potential endogeneity of climate variables with respect to Chinese grain cultivation.

Our results have several implications for Chinese agricultural and climate-related policies. Since additional land for agricultural production, which has the highest output elasticity, is severely constrained in China, the government has to resort to other more readily available measures to promote an expansion of output. Even though their marginal contributions are not very large, both increasing the use of fertilizer and of agricultural machinery seem to be promising strategies according to our results if one

were to neglect the potentially adverse impacts of further increments in fertilizer application and energy use on the environment. Furthermore, neither of these two input factors features a positive and significant marginal contribution to production risk.

The main result with respect to the influences of climate and its change over time are that China might actually be a net beneficiary of climate change in the short or medium run, though there will certainly be regional winners and losers within the country. Particularly an increase in average annual temperatures at the margin will have a positive impact on mean output and will in addition reduce the level of production risk. The role of an increase in precipitation, which is expected in the future, is somewhat less clear. While it also seems that it will decrease production risk at the margin, its influence on mean output remains ambiguous. The variability of temperature again has a positive effect on mean output but doesn't seem to affect production risk. Considering all these influences together, we arrive at the conclusion that China should be able to keep up its food production in the near future and, drawing on our earlier calculations, expect that the country will even be able realize an economic benefit of around $1.1 billion from a 1 °C increase in annual average temperature. However, we expect the positive net gains to be of temporary nature. Since all crops feature certain ranges of climate conditions, in which they can grow optimally, a continued change in these conditions will, with high probability, eventually lead China to a point where the net benefits from climate change will turn negative. Since the point in time when this happens is not known, it would be an advisable strategy for China to start investing in region-specific adaption measures as soon as possible.

Our approach of testing for an endogeneity of climate factors reveals that climate change is an exogenous factor in Chinese grain production, which implies that the feedback effects of grain cultivation on climate are not significant and has important implications for Chinese agricultural policy making.

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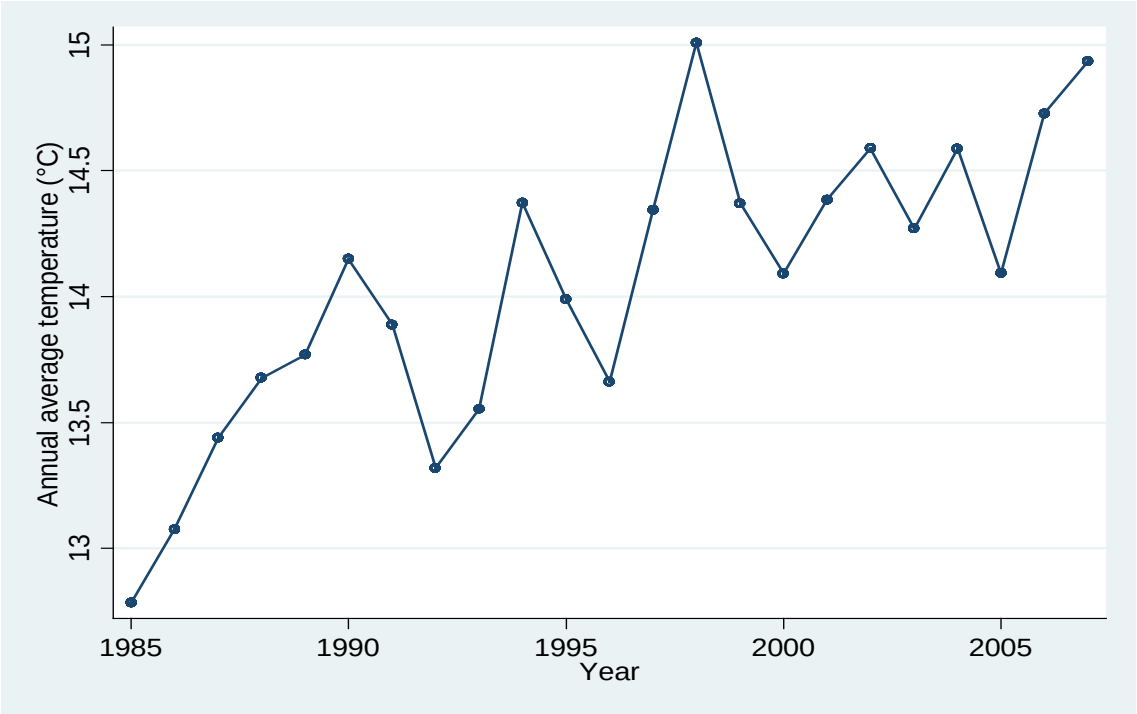
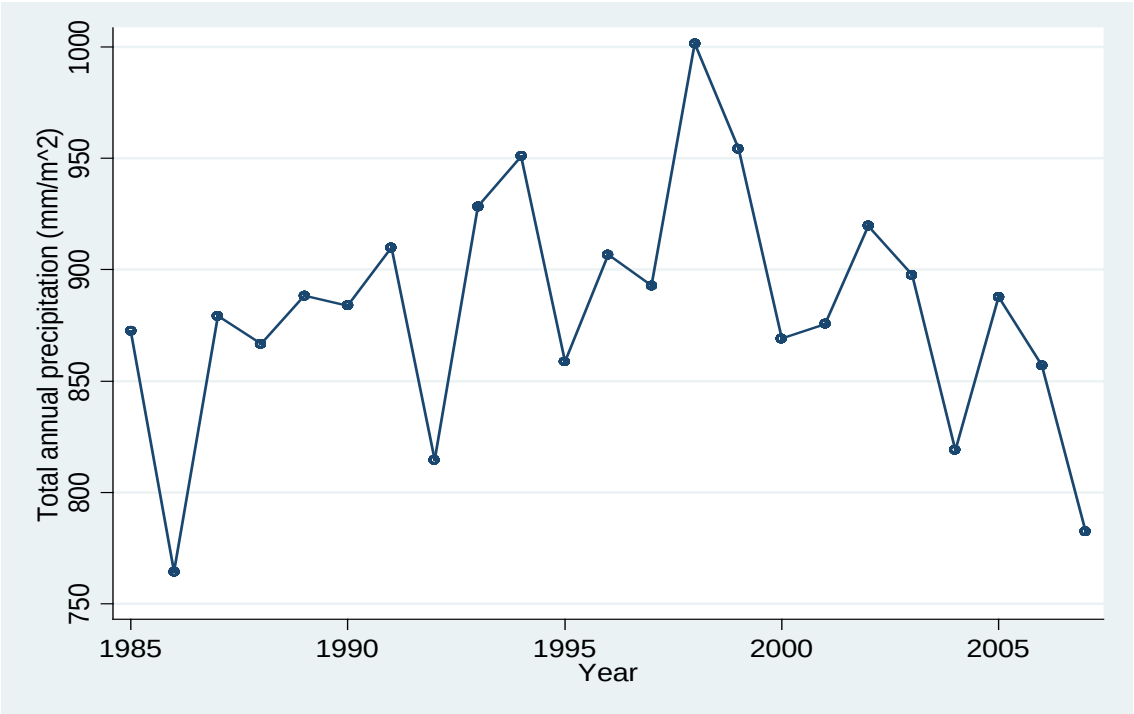
Figure 1: Changes in Annual Average Temperatures in China over Time (national average)



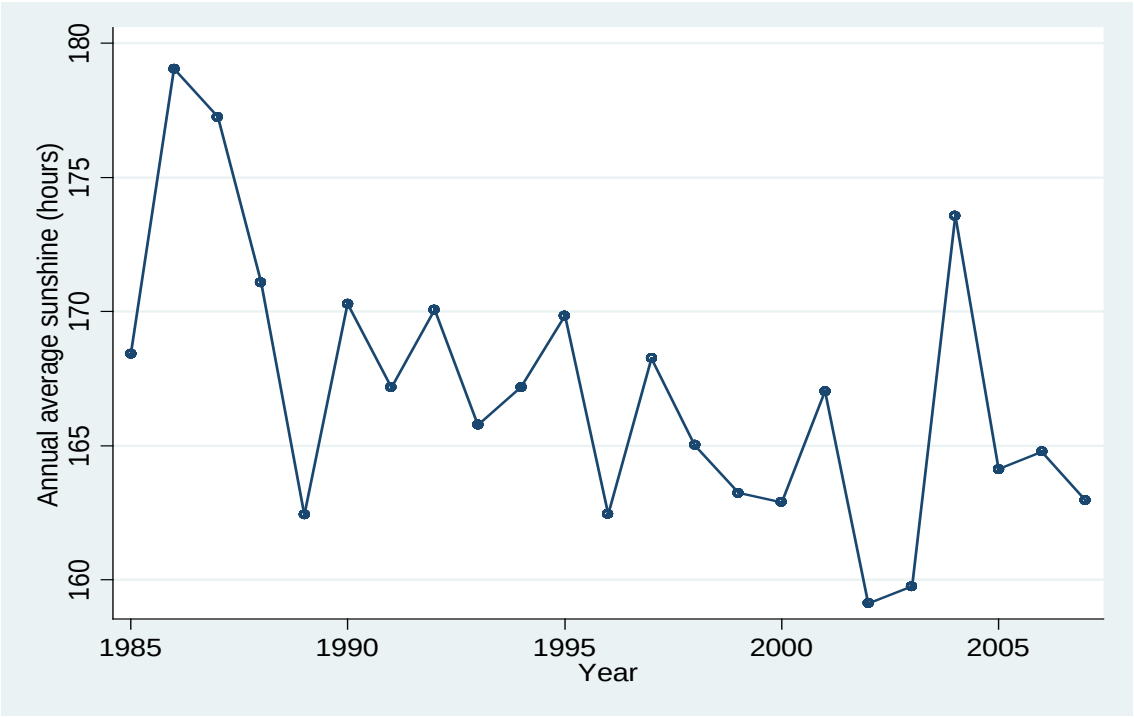
Data sources: National Bureau of Statistics of China, 1986-2008

Figure 2: Changes in Total Annual Precipitation Levels in China over Time (national average)



Data sources: National Bureau of Statistics of China, 1986-2008

Figure 3: Changes in Annual Average Durations of Sunshine in China over Time (national average)



Data sources: National Bureau of Statistics of China, 1986-2008

Table 1: Regression Results

	I	II	III	IV	
	C-D (FE)[a]	C-D (FGLS)[b]	C-D (FGLS)[c]	J-P Mean (NLS)	J-P Risk (FE)
DEPENDENT VARIABLE:	ln grain	ln grain	ln grain	grain	ln grain
(ln) grain area	1.059	0.795	0.79	0.995	-1.078
	(25.35)***	(25.56)***	(27.12)***	(23.23)***	(-2.25)**
(ln) irrigation	0.016	0.012	0.029	-0.016	0.246
	(1.08)	(1.20)	(2.67)***	(-1.06)	(1.4)
(ln) fertilizer	0.13	0.18	0.183	0.13	0.237
	(7.51)***	(7.60)***	(7.54)***	(7.04)***	(1.18)
(ln) labor	0.036	0.063	0.027	0.014	0.164
	(2.01)**	(2.97)***	(1.23)	(0.93)	(0.8)
(ln) machinery	0.141	0.072	0.082	0.067	0.008
	(8.54)***	(3.28)***	(3.75)***	(4.45)***	(0.04)
(ln) temperature average			0.063	0.156	-2.015
			(1.65)*	(2.07)**	(-2.22)**
(ln) precipitation total			0.055	0.026	-0.451
			(3.56)***	(1.39)	(-1.78)*
(ln) sunshine average			-0.057	-0.045	0.496
			(-1.72)*	(-1.22)	(0.8)
(ln) temperature deviation			0.044	0.052	-0.255
			(3.80)***	(3.53)***	(-1.44)
(ln) precipitation deviation			-0.011	-0.005	0.31
			(-0.84)	(-0.35)	(1.63)
(ln) sunshine deviation			-0.001	-0.025	-0.283
			(-0.08)	(-1.38)	(-1.25)
Constant	-3.106	-0.843	-1.076	-2.148	15.305
	(-8.93)***	(-5.21)***	(-3.65)***	(-3.69)***	(2.58)**
Observations	552	552	551	551	551
Number of Index	26	26	26		26
R-squared	0.67			0.99	0.04

* significant at 10%; ** significant at 5%; *** significant at 1%

a: A Breusch and Pagan LM test on the corresponding RE model led to the rejection of pooled estimation using OLS. Test statistic: chi2(1) = 2460.57 ; prob > chi2 = 0.0000

b: FGLS warranted because the corresponding FE model has been found to be affected by serial correlation. Results of regressing the error term of the FE model on its own one-year lag: Coefficient: 0.3375; Standard Error: 0.4148; t statistic: 8.14; P-value: 0.000

c: FGLS warranted because the corresponding FE model has been found to be affected by serial correlation. Results of regressing the error term of the FE model on its own one-year lag: Coefficient: 0.3202; Standard Error: 0.0424; t statistic: 7.56; P-value: 0.000

I, IV, V: Absolute value of t statistics in parentheses

II, III: Absolute value of z statistics in parentheses

I, II, III, V: Logarithmic inputs

IV: Non-logarithmic inputs