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Climate Change, Risk and Grain Production in China

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

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Climate Change, Risk and Grain Production in China

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 potential endogeneity of climate factors in Chinese grain production. Our results indicate that grain production in south China might, at least in the short run, could be a net beneficiary of global warming. In particular, we find that a 1 °C increase in annual average temperature in South China could entail an increase of grain output by 3.79 million tons or an economic benefit of around USD 798 million due to the increasing mean output. However the impact of global warming in north China is negative, small and insignificant. In addition, Hausman tests reveal 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 decisions, 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), Wang et al. (2008), 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 literature.

The world climate is changing (IPCC, 2007; Shortle et al., 2009; Parry et al., 2007), and the consequences of this are and also 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 could harm agricultural production some developing countries in Africa and South America (Mendelsohn, 2009; Féres et al., 2008). Even though Mendelsohn (2009) also find that global warming could be harmful to Chinese famers in general, Wang et al. (2008) conclude that global warming is only harmfaul to non-irrigation farmers, but beneficial to irrigation farmers. 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^{o}C.

As shown in Figures 1 to 3, China is not spared from climate changes and its grain production to a considerable extent depends on the development of the regional and the global climate. Regressions of the climate variables against time furthermore find the increases in annual average temperature and annual average duration of sunshine depicted are highly significant (Table 1). In addition, 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 and droughts (Smit and Cai, 1996). It is generally expected that climatic variability in terms of such extreme weather events will increase in the foreseeable future, except that mean climate conditions are also forecasted to change. Following a gradual warming over the past five decades, East Asia is expected to experience a further substantial increase in annual average temperatures until 2100 (IPCC, 2007). Moreover, 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, but Wang et al. (2008) conclude that global warming is only harmfaul to non-irrigation farmers, but beneficial to irrigation farmers. Wang et al.(2010) also give a comprehensive review for the impact of climate change on Chinese agriculture in which the results are inconclusive. The current lieterature in this field only focuses on the impact of mean temperature shifting, and the impact of the volatility is however neglected.

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 force 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 not only for China but for other countries as well.

However, scientific evidence has also shown that agricultural production may impact climate through landscape changes, the application of chemical inputs, the use of 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 sources of GHG emissions 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 somehow 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 (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 in 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 the 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; Wang et al. 2008) per unit of land. However, there are some unobserved heterogeneities in error terms when using the Ricardian method, for example some inputs (e.g. fertilizers), landscape, or soil quality (Deschênes and

Greenstone, 2007), which can be correlated with climate variables. This causes endogeneity problems in regressions and hence leads to inconsistent estimation.

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. Even though Wang et al. (2008) use Ricardian Methods with farmers' net income as dependent variables, some important variables such as the land prices or rent, and food prices are not included which may cause bias in estimation. 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, and provides some insights for the impacts of climate on food security directly in a short run as well. 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. 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 a 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) $$\ln y_{it} = \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_{kit} \ ,$$

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

An important precondition for the consistency of the fixed-effects 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 heteroskedasticity in the production function. They furthermore point out that many common specifications of production functions, which do not specifically consider risk, are characterized by the strong constraint that they only allow the variance of output to be always positively correlated with inputs which is obviously unrealistic. Following Just

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

and Pope (1978, 1979), we develop a non-linear fixed-effects 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 equation (3) 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 (3): (1) Non-linear least squares estimation of the mean output function, (2) estimation of the risk function using a fixed-effects model, and (3) re-estimation of the mean output function utilizing a generalized non-linear least squares model.

China's provinces are usually considered to be quite heterogeneous in terms of geographical features, climate regimes, economic development and other aspects. If these heterogeneities should have a significant impact on grain production, it would necessitate to specify the models of stages (1) and (3) of the above procedure as fixed effects models by including a dummy variable for each province, which in turn would result in a significantly better fit to the data. An F-test comparing the regressions with and without province dummies on stage (3) will be informative with respect to the necessity of this approach.

However, since one of the defining heterogeneities in Chinese agriculture, the climatic difference between the country's subtropical south and its temperate northern part, is likely to make a difference with respect to the impact of climate change, as shown by Wang et al.(2008), we want to specifically analyze to what extent the marginal contributions of standard physical and climate inputs to mean output and to production risk differ between the two regions. We therefore split the sample into northern and southern provinces and separately apply the Just-Pope procedure to those subsamples. We also again test for the necessity of including province dummies into the regressions.

2.5 Impact Analysis

Another important matter is to calculate the costs or benefits of climate change because this holds 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 temperature), 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 (stage 3). This equation thus quantifies the economic impacts of a marginal change in climate.

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[2], cultivation area, rural 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

[2] Aggregate grain output measured by weight, as reported by the National Bureau of Statistics of China (NBS), consists of the individual output quantities of the different varieties of rice, wheat, corn, sorghum, millet, tubers and beans. The total weight of harvested tubers (net of the share recorded as vegetables) has been converted by the NBS to grain-equivalent output by assuming that five kilograms of tubers are equivalent to one kilogram of the other grains (National Bureau of Statistics of China, 2008).

and machine power as well as the size of the irrigated area used for the production of grain, the total input quantities have been multiplied with the share of the grain cropping area in total cropland, which entails the simplifying assumption of equal input use per unit area of land for all crops. In the cases of labor and machinery, we furthermore acknowledge that these inputs are also substantially used in agricultural sectors other than crop cultivation. Consequently, we adjust them a second time by also multiplying them with the share of crop output value in total agricultural output value. Similar adjustment procedures have also been applied by Zhang and Carter (1997) and Lin (1992) respectively.

For each of the above climate factors, we construct variables representing their first and second central moments. First moment variables 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, as we assume farmers in China might have some ability to adapt to climate changes. 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 Tables 2 and 3, which include 9 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; and Models IV-IX are the estimation results of the Just-Pope models previously described. Each of them features a mean production function and a risk function.

F-tests reject the null-hypothesis of there being no significant difference between the provinces based on the full sample of provinces as well as based on the northern and southern sub-sample. The corresponding F-ratios are 9.59 (p-value: 0.000), 9.57 (p-value: 0.000) and 9.10 (p-value: 0.000), respectively. Therefore, irrespective of the sample chosen, the introduction of province dummies is warranted.

In particular, comparing the results of the mean production functions in Model III and Model Va, we find that in both models the coefficients of all physical input factors are significant. However, labor is only weakly significant in Model III while it is highly significant in Model Va. With respect to climate influences, Model III finds total precipitation, average duration of sunshine and the deviation of temperature to be highly significant. Model Va in turn yields only a weak significance for total precipitation and a high level of significance for the deviation of temperature. The variables representing annual average temperature and the deviations of precipitation and sunshine are not statistically significant in either model.

As we know, the Just-Pope model is superior to the approaches in Models I-III because it explicitly captures risks in production, which play crucial roles in agriculture. The coefficients of the other models, which do not analyze risk factors, may mix up the contributions to mean output and to production risk. Hence, the Just-Pope model is our preferred approach.

The patterns of agricultural production in South China are substantially different from those in the north. The main grain in South China is rice and usually more than one cropping season is possible in this part of the country, while the main grain in North China, where usually only one cropping season is possible, is wheat. Agricultural scientists found that rice prefers high temperatures, a high-humidity and short durations of sunshine, while wheat grows better under long durations of sunshine and a relatively dry weather. In order to capture the structural differences between South and North China, we also estimated the Just-Pope model separately for each of these two regions. The corresponding results are reported in Table 3 and given the above considerations, the following discussions will focus on models VII (subsample of northern provinces) and IX (subsample of southern provinces), both of which are specified with dummy variables representing the provincial different.

- 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. Based on our preferred Just-Pope models, it features an output elasticity of 0.5105 for the north of the country (Model VIIa) and 0.8259 for the south (Model IXa). Both results are significant at the 1%-level. Compared to land, the magnitude of all other estimated coefficients is rather small. The considerably higher output elasticity with respect to land 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 Cai, 1996).

Fertilizer and Machinery also positively and significantly contribute to grain production in the north and south of China, though to varying degrees as it comes to the estimated output elasticities. Specifically, the estimation results of the Just-Pope model show that the output elasticity with respect to fertilizer is 0.163 in the north and 0.0884 in the south. Both results are statistically significant at the 1% level. As aforementioned, China features one of the most fertilizer-intensive agricultural sectors in the world. Nevertheless, the small marginal contributions of fertilizer obtained here are still positive. The output elasticities with respect to machinery are 0.1578 and 0.1537 in the north and the south respectively and are also statistically significant at the 1% level. In China, the agricultural 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 as compared to the output elasticity with respect to land but still significant.

However, an incremental in agricultural labor even has a much smaller impact on marginal output in the Northern provinces, whereas the corresponding effect in the south is somewhat larger than that of machinery. Particularly the result for the north 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, with a point estimate of only 0.0407, very small.

With respect to the area under irrigation we find the impacts in North China to be contrary to those in the south of China. Model VIIa yields positive and significant output elasticity with respect to irrigation for the Northern provinces. Thus, despite the fact that Northern China is less richly endowed with water resources than the south, expanding irrigation systems, which in some northern regions are at least in part fed by groundwater, can obviously still have a positive impact on grain production, even though it has already been observed that the continued use of groundwater for irrigation purposes has led to a drastic lowering of the ground water table in some regions, like the North China Plain (Smit and Cai, 1996). However, for the subsample consisting only of the southern provinces we find a small but highly significant negative marginal impact on mean output, which could be explained by the circumstance that water, especially due to higher levels of precipitation, is much more abundant in the south of China than it is in the north..

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 for the southern provinces but no significant result for the northern half of the country. It is plausible that a small increase in temperature in south China can significantly increase the output of rice, which is the predominantly grown grain in that region, but does not have the same impact on wheat, which dominates in North China, as wheat prefers lower temperatures than rice. In particular, we find the elasticity of output with respect to temperature in the south to be 0.2642, which, together with the fact that we find small negative and insignificant impact for the north, indicates that China in general might benefit from higher annual average temperatures. The results are consistent with Wang et al.(2008) in which global warming is beneficial to irrigation farmers but mildly harmful to non-irrigation farmers. This would ceteris paribus make China a net beneficiary of global warming. 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 results just described and using equation (4), we can calculate the economic benefit of global warming with respect to grain production in South China. Given an average temperature of 18.7°C[3] in the capital cities of China's 14 southern provinces in 2007, a grain output of 267,8 million tons[4] in that part of the country so that the marginal output of temperature will be 3.786 million tons of grains. Given an average grain price of 1.598 yuan/kg[5], the shadow price of temperature in South China is:

$$w_T = \text{CNY 6.05 billion}$$
$$\approx \text{USD 798 million}^{6},$$

which implies that the benefit of a global warming of 1 °C accruing to grain production in South China would have a value of USD 798 million[7]. Table 4 presents the values of

[3] Source: China Statistical Yearbook 2008, Tables 11-13 (National Bureau of Statistics of China, 2008).
[4] Source: China Statistical Yearbook 2008, Tables 12-2 (National Bureau of Statistics of China, 2008).
[5] Source: Shandong Development and Reform Commission, http://www.sdjw.gov.cn/show.asp?type=zwgk&id=228
[6] Exchange rate: USD 1 = CNY 7.581127 (2007).
[7] Based on the estimates for the full set of provinces, the corresponding value would be USD 631.8 million. However, this result is insignificant.

ceteris paribus marginal changes in all considered climate variables for China as whole as well as for North and South China separately.

The estimated coefficients of the total precipitation regarding the north and the south are very close. They amount to 0.044 and 0.047, respectively. However, only in the case of South China the result is statistically significant, which again might be caused by differences in crop structure because rice is very sensitive to changes in water availability, whereas wheat is less sensitive in this respect.

With respect to our second central moment climate variables, only the variability measure of temperature turns out to be positive and significant in the case of the Northern provinces. At first glance, this result is contrary to common wisdom because strong or frequent positive or negative deviations from average temperatures, 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 increase the output of many crops. Particularly winter wheat, which is common in Northern China, is known to benefit from such variability as it needs a cold period of limited duration in order to flower properly in spring.

For the south of China we find the elasticity of output with respect to the variability measure of precipitation to be -0.0356, which is statistically significant at the 5%-level, whereas the output elasticity of the variability measure of the duration of sunshine is significant at the 10%-level and features a coefficient of 0.0431. This could be explained by the fact that rice not only prefers a climate characterized by high humidity but also short periods of sunshine.

- Risk Function

Our analyses of production risk in Chinese grain farming by means of Just and Pope's procedure (Models VIIb and IXb for the northern and southern provinces, respectively) reveal that agricultural machinery in South China is the only physical input factor, which is associated with a significant risk elasticity. We attribute its risk-decreasing impact to the fact that the use of machinery allows for a more efficient and speedy execution of many tasks in agriculture, which should reduce farmers' exposure to risks for example stemming from adverse weather events during the harvest season or from pest or fungal infestations.

Climate factors also turn out to significantly affect production risk in Chinese grain farming. However, we again only find this for the southern provinces. The risk elasticity with respect to the deviation of precipitation from the long-term average in this region of the country is strongly positive and highly significant. Again we explain this by the fact that rice, which is the predominant grain in South China, needs a high-humidity climate and in particular a steady water supply. Hence fluctuations of precipitation are not good for rice production as they could increase the level of production risk in rice cultivation.

Furthermore, we find a significant risk-decreasing marginal effect of the deviation of the duration of sunshine from its long-term average in the case of South China. Again this might be rooted in the fact that rice prefers short periods of sunshine, so that a higher degree of variability in this climate factor might decrease production risk stemming from overly long exposures to sunshine (i.e. solar radiation).

- Endogeneity

Finally, for the reasons discussed earlier, we are concerned about the possible endogeneity of climate variables in the present context both from an econometric and from a policy perspective. We therefore separately use one-year and two-year lags of the climate variables as instruments to estimate Equation (1) with climate variables included. Hausman tests (Hausman, 1978) however cannot reject the null hypothesis of there being no systematic difference between the fixed-effects model and the two IV regressions respectively for all provinces, Southern Provinces and Northern Provinces. 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 grain production 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 separately determine each input factor's marginal contribution to mean output and to production risk. 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 as compared to land, based on the responsiveness of output, increasing the use of labor, irrigation, fertilizer and agricultural machinery all seem to be promising strategies both in the north and the south of the country. However, further increments in the application fertilizer could have adverse impacts on the environment (e.g. by polluting the ground water) and increasing the cultivation area under irrigation might in some regions also be a questionable strategy because it would put additional pressure on already constrained water resources, thereby potentially reducing the efficiency of all irrigation systems in that region. In any case, neither of these input factors features a positive and significant marginal contribution to production risk, which would be an argument against increasing the use of an input factor.

The main results with respect to the influences of climate and its change over time are that China might actually be a net beneficiary of the projected changes in climate in the short run. Particularly an increase in annual average temperatures will at the margin have a positive impact on mean output in South China, while an increased deviation of temperature will benefit the north of the country. Furthermore, no temperature-related variable has a significant impact on production risk. The role of an increase in precipitation, which is expected in the future, is somewhat less clear. Higher levels of total annual precipitation will benefit the southern provinces in terms of mean output but have no significant impact on grain production in China's northern regions. Consequently, even though the deviation of precipitation from its long-term average has a significant risk-increasing effect, 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, stemming from benefits in South China, might even be able realize an economic benefit of around USD 798 million from a 1 °C increase in annual average temperature. We attribute the difference between South and North China mainly to the different crop structures in the two regions of the country. It is well known that rice, which is the predominantly grown grain in South China, prefers a climate characterized by high temperatures, high humidity levels and short durations of sunshine, whereas wheat, which is the main crop in North China, prefers lower temperatures and a rather dry climate. Our results are highly consistent with the current literature, for example Wang et al (2008).

Since all our results represent marginal effects and thus pertain only to the short-run and since it also known that all crops feature certain ranges of climate conditions, in which they can grow optimally, a continued change in these conditions might eventually lead China to a point where the net benefits from climate change may turn negative.

Our approach of testing for a potential endogeneity of climate factors reveals that climate change is an exogenous factor in Chinese grain production, which implies that the feedback effects of Chinese grain cultivation on climate are not significant. Eventually the finds in this study will have insightful implications for Chinese agricultural policy making.

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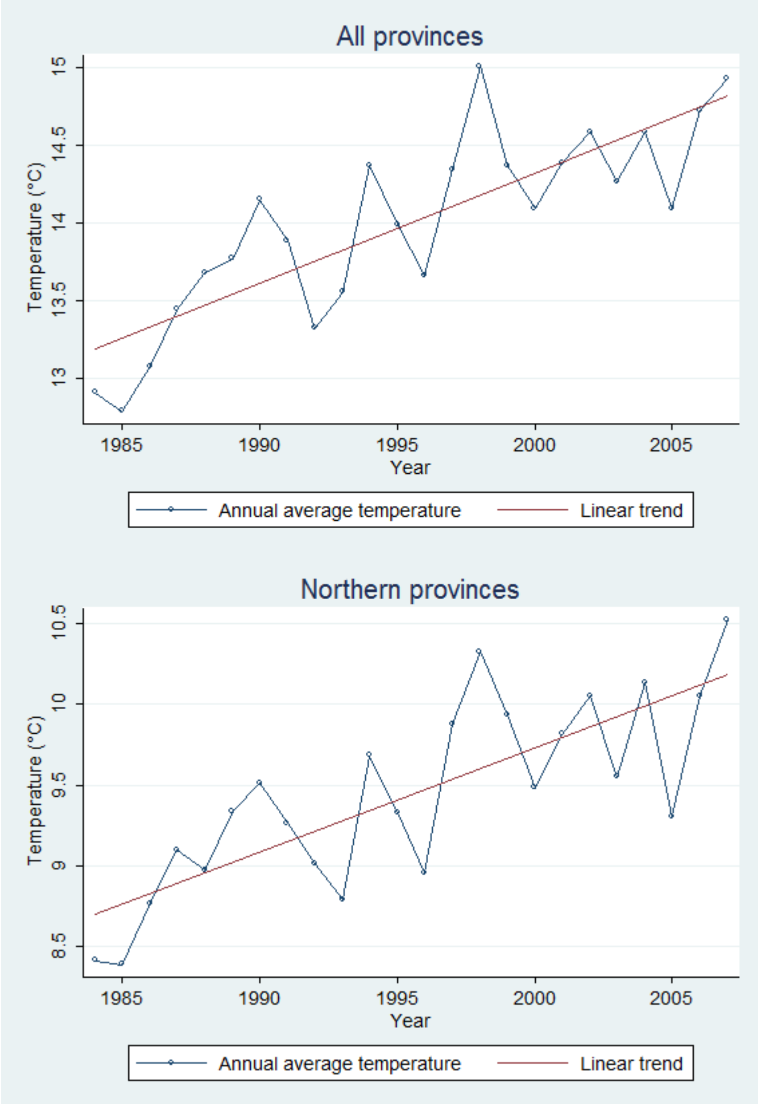
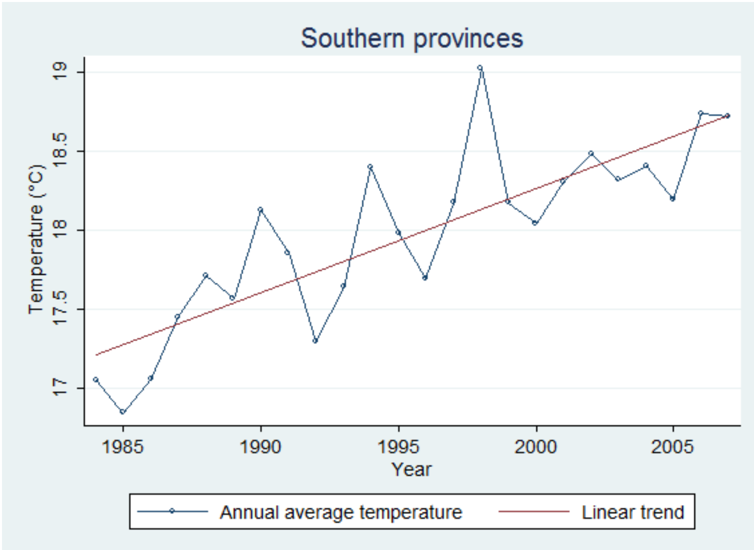
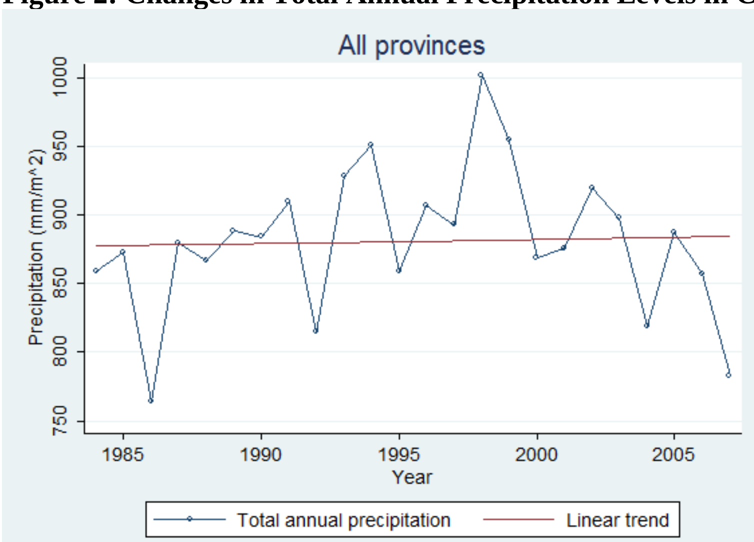
Figure 1: Changes in Annual Average Temperatures in China over Time

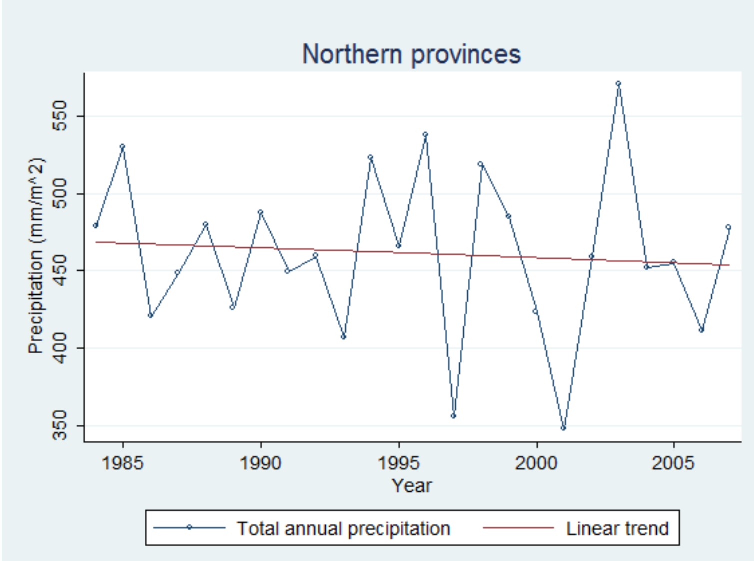


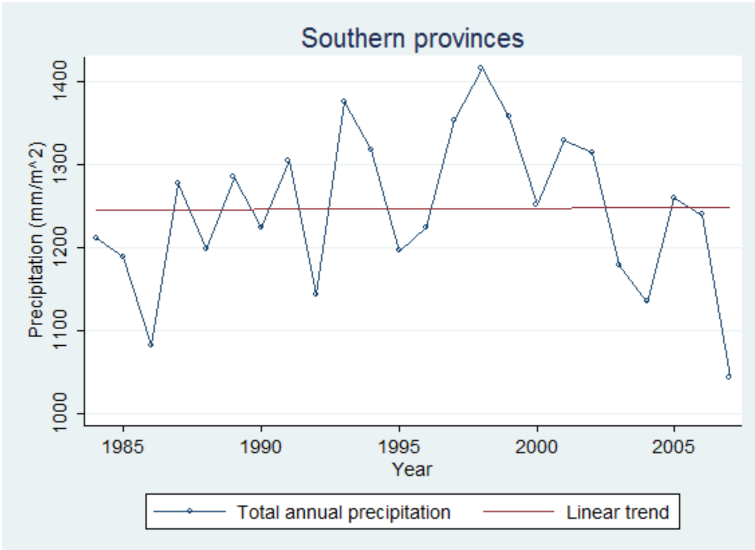


Source: Own calculations; Data: National Bureau of Statistics of China, 1985-2008

Figure 2: Changes in Total Annual Precipitation Levels in China over Time

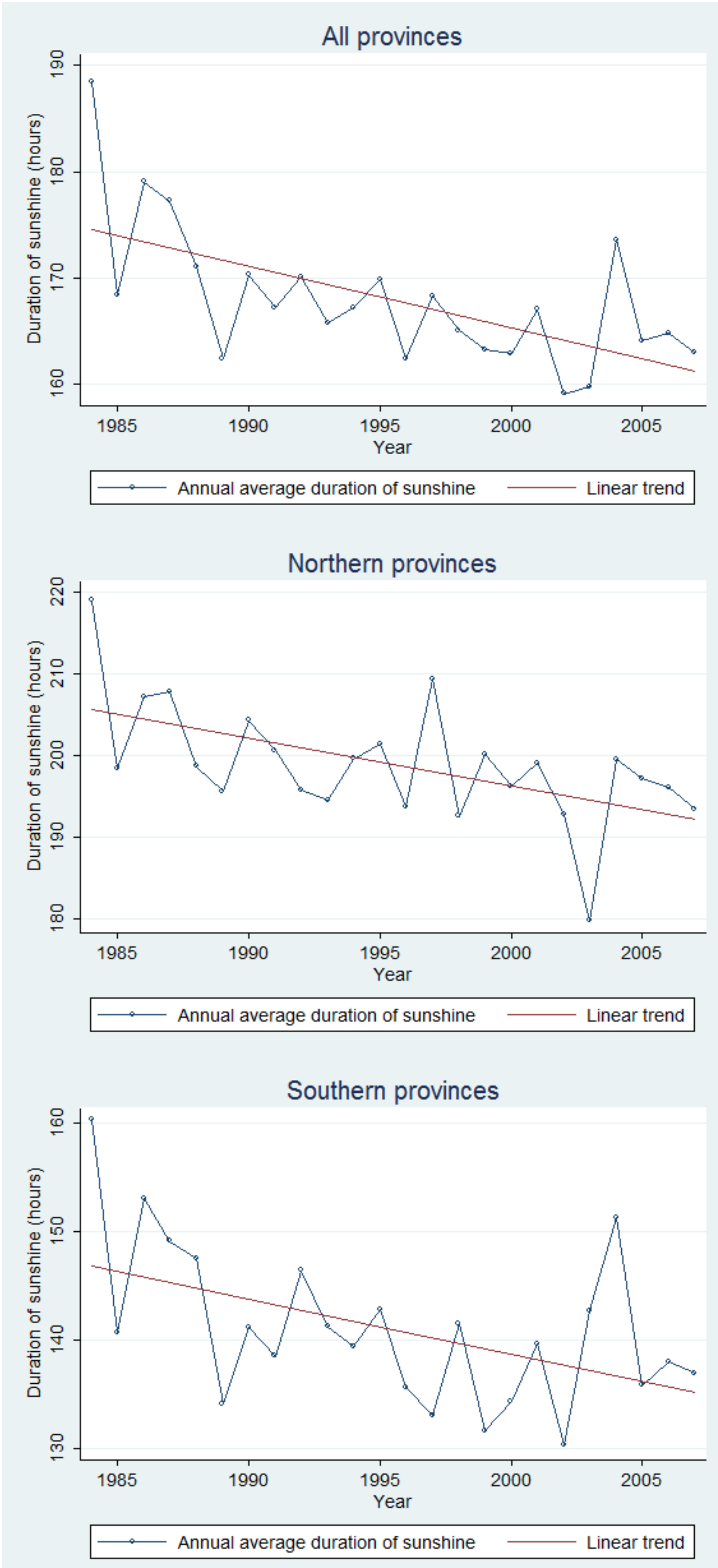






Source: Own calculations; Data: National Bureau of Statistics of China, 1985-2008

Figure 3: Changes in Annual Average Durations of Sunshine in China over Time



Source: Own calculations; Data: National Bureau of Statistics of China, 1985-2008

Table 1: Regressions of Major Climate Factors on their Respective Linear Time Trends

	All provinces	Northern provinces	Southern provinces
Model	i	ii	iii
Dependent variable	*Anual average temperature*	*Anual average temperature*	*Anual average temperature*
Linear time trend	0.0712	0.0646	0.0660
	(36.52)***	(21.84)***	(26.48)***
Constant	13.1112	8.6350	17.1432
	(469.42)***	(204.36)***	(478.88)***
Observations	620	288	332
R-squared	0.68	0.63	0.68
Number of Provinces	26	12	14
Model	iv	v	vi
Dependent variable	*Total annual precipitation*	*Total annual precipitation*	*Total annual precipitation*
Linear time trend	0.3291	-0.6388	0.1767
	(1.09)	(-1.43)	(0.24)
Constant	876.9335	469.3259	1243.9280
	(203.36)***	(73.58)***	(119)***
Observations	620	288	332
R-squared	0.00	0.01	0.00
Number of Provinces	26	12	14
Model	vii	viii	ix
Dependent variable	*Annual average sunshine*	*Annual average sunshine*	*Annual average sunshine*
Linear time trend	-0.5816	-0.5843	-0.5054
	(-19.94)***	(-11.34)***	(-10.29)***
Constant	175.1702	206.1763	147.2677
	(418.92)***	(280.11)***	(208.67)***
Observations	620	288	332
R-squared	0.39	0.31	0.24
Number of Provinces	26	12	14

Source: Own calculations
Data: National Bureau of Statistics of China, 1985-2008

Table 2: Analysis of Chinese Grain Production (Part 1)

Model	*I*	*II*	*III*	*IV a*	*IV b*	*V a*	*V b*
	Production Function	Production Function	Production Function	J-P Method (All prov., no dummies)		J-P Method (All prov., incl. dummies)	
				Mean Function	Risk Function	Mean Function	Risk Function
	(FE)	(FGLS)	(FGLS)	(NLS)	(FE)	(NLS)	(FE)
Dependent Variable	*ln (grain output)*	*ln (grain output)*	*ln (grain output)*	*adj. grain output*	*production risk*	*adj. grain output*	*production risk*
Area	0.8470	0.7112	0.7043	0.8447	0.6403	0.9216	-0.3749
	(20.00)***	(18.68)***	(20.96)***	(31.13)***	(1.64)*	(21.03)***	(-0.86)
Labor	0.0325	0.0912	0.0378	0.0041	-0.1243	0.0964	-0.4077
	(1.93)*	(4.14)***	(1.78)*	(0.22)	(-0.81)	(2.89)***	(-2.38)**
Irrigation	0.0220	0.0211	0.0547	0.0337	-0.2268	-0.0523	0.2274
	(1.45)	(1.73)*	(4.00)***	(4.28)***	(-1.63)	(-2.77)***	(1.46)
Machinery	0.2457	0.0926	0.0788	-0.0556	-0.1479	0.1336	-0.1145
	(11.76)***	(3.72)***	(3.38)***	(-3.29)***	(-0.74)	(7.51)***	(-0.51)
Fertilizer	0.1256	0.1870	0.2243	0.3094	0.6215	0.1513	0.1812
	(7.23)***	(7.64)***	(9.32)***	(18.38)***	(3.84)***	(8.20)***	(1.00)
Average temperature			0.0588	0.0606	-0.3621	0.0920	-0.9523
			(1.56)	(1.83)*	(-0.51)	(1.41)	(-1.21)
Total precipitation			0.0687	0.1446	0.0444	0.0297	-0.1397
			(4.26)***	(6.76)***	(0.22)	(1.77)*	(-0.63)
Average sunshine			-0.0918	-0.0204	0.5917	-0.0406	0.5212
			(-2.76)***	(-0.67)	(1.24)	(-1.16)	(0.98)
Temperature deviation			0.0468	0.0931	-0.3120	0.0404	-0.3204
			(3.77)***	(4.54)***	(-2.23)**	(2.89)***	(-2.05)**
Precipitation deviation			-0.0118	0.0019	-0.0428	-0.0079	0.3254
			(-0.89)	(0.09)	(-0.29)	(-0.61)	(1.95)*
Sunshine deviation			-0.0076	-0.0906	-0.1736	-0.0182	-0.2672
			(-0.43)	(-3.70)***	(-0.97)	(-1.09)	(-1.34)
Constant	-2.1254	-0.6686	-0.7564	-1.6865	-0.1256	-2.3113	9.2160
	(-6.59)***	(-3.83)***	(-2.49)**	(-5.59)***	(-0.03)	(-4.76)***	(1.82)*
Observations	552	552	551	551	551	551	551
R-squared	0.677			0.98	0.05	0.99	0.04
Number of Provinces	26	26	26	26	26	26	26

Source: Own calculations
Data: National Bureau of Statistics of China, 1985-2008

Table 3: Analysis of Chinese Grain Production (Part 2)

Model	*VI a*	*VI b*	*VII a*	*VII b*	*VIII a*	*VIII b*	*IX a*	*IX b*
	J-P Method (North, no dummies)		J-P Method (North, incl. dummies)		J-P Method (South, no dummies)		J-P Method (South, incl. dummies)	
	Mean Function (NLS)	Risk Function (FE)	Mean Function (NLS)	Risk Function (FE)	Mean Function (NLS)	Risk Function (FE)	Mean Function (NLS)	Risk Function (FE)
Dependent Variable	*adj. grain output*	*production risk*	*adj. grain output*	*production risk*	*adj. grain output*	*production risk*	*adj. grain output*	*production risk*
Area	0.5349	-3.7373	0.5105	-0.6304	0.9753	-0.2532	0.8259	-0.3793
	(13.19)***	(-3.05)***	(5.51)***	(-0.59)	(21.91)***	(-0.44)	(16.17)***	(-0.48)
Labor	0.0535	0.0737	0.0407	-0.0307	-0.0792	0.4214	0.2126	-1.1837
	(2.82)***	(0.4)	(2.36)**	(-0.19)	(-1.84)*	(0.65)	(3.89)***	(-1.34)
Irrigation	0.1941	1.4080	0.2216	0.6825	0.0300	-0.1601	-0.0629	0.2319
	(5.61)***	(2.58)***	(3.28)***	(1.44)	(4.36)***	(-1.24)	(-3.6)***	(1.33)
Machinery	0.0232	0.4324	0.1578	-0.1038	0.0956	-0.0122	0.1537	-0.6541
	(0.87)	(1.04)	(3.96)***	(-0.29)	(4.56)***	(-0.06)	(6.71)***	(-2.25)**
Fertilizer	0.3458	0.3395	0.1630	-0.2302	0.1349	0.2571	0.0884	0.2868
	(19.66)***	(1.09)	(3.71)***	(-0.85)	(5.91)***	(1.39)	(4.1)***	(1.15)
Average temperature	-0.2066	-1.0512	-0.0869	-0.5869	0.1116	0.4103	0.2642	-2.2633
	(-3.99)***	(-1.06)	(-0.8)	(-0.68)	(1.61)	(0.26)	(2.58)***	(-1.05)
Total precipitation	-0.1204	0.0571	0.0441	0.3322	0.1021	-0.2335	0.0473	-0.2425
	(3.47)***	(0.18)	(1.52)	(1.19)	(3.81)***	(-0.91)	(2.16)**	(-0.70)
Average sunshine	0.1748	1.0029	-0.0075	-0.8414	-0.1174	0.2909	-0.1080	0.6452
	(2.38)**	(1.12)	(-0.09)	(-1.08)	(-3.86)	(0.53)	(-3.07)***	(0.87)
Temperature deviation	0.1276	-0.4931	0.0436	0.0296	0.0070	-0.1589	0.0062	-0.2610
	(4.88)***	(-2.2)**	(1.91)*	(0.15)	(0.29)	(-0.86)	(0.36)	(-1.04)
Precipitation deviation	0.0031	-0.0507	-0.0043	-0.2315	0.0087	0.0312	-0.0356	0.6832
	(0.11)	(-0.21)	(-0.2)	(-1.08)	(0.39)	(0.17)	(-2.13)**	(2.77)***
Sunshine deviation	-0.1360	-0.0099	-0.0378	-0.1017	0.0363	-0.0649	0.0431	-0.5948
	(-4.17)***	(-0.03)	(-1.41)	(-0.41)	(1.22)	(-0.28)	(1.84)*	(-1.91)*
Constant	-1.3744	18.6042	-0.4507	11.8394	-2.2563	3.7563	-2.4107	20.7504
	(-2.26)**	(1.74)*	(-0.5)	(1.27)	(-5.61)***	(0.53)	(-4.38)***	(2.18)**
Observations	247	247	247	247	304	304	304	304
R-squared	0.99	0.12	0.96	0.04	0.99	0.03	0.98	0.09
Number of Provinces	12	12	12	12	14	14	14	14

Source: Own calculations

Data: National Bureau of Statistics of China, 1985-2008

Notes on Tables 2 and 3

Absolute value of t statistics in parentheses: Models I, IV-XV
Absolute value of z statistics in parentheses: Models II-III

Logarithmic independent variables: Models I-III, IVb, Vb, VIb, VIIb, VIIIb, IXb
Non-logarithmic independent variables:Models IVa, Va, VIa, VIIa, VIIIa, IXa

Table 4: Benefits of marginal changes in the different climate variables (ceteris paribus)

	Nation		North China		South China	
	Output elasticity	Benefit (billion yuan)	Output elasticity	Benefit (billion yuan)	Output elasticity	Benefit (billion yuan)
Annual average temperature	0.092	4.79	-0.0869	-2.88	0.2642 ***	6.04
Total annual precipitation	0.0297 *	0.03	0.0441	-0.03	0.0473 **	0.02
Annual average sunshine	-0.0406	-0.19	-0.0075	-0.01	-0.108 ***	0.34
Temperature deviation	0.0404 ***	2.73	0.0436 *	1.29	0.0062	0.23
Precipitation deviation	-0.0079	-0.02	-0.0043	-0.01	-0.0356 **	-0.03
Sunshine deviation	-0.0182	-0.05	-0.0378	-0.05	0.0431 *	0.06

Assumed grain price: CNY 1.598/kg

Source: Own calculations
Data: National Bureau of Statistics of China, 1985-2008