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Quantifying the Temperature Effects on China's Total Agricultural Output

Xiaoguang Chen and Jue Du



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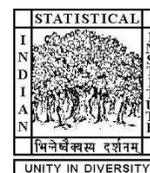
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Quantifying the Temperature Effects on China's Total Agricultural Output

Xiaoguang Chen and Jue Du*

Abstract

We pair a county-level panel of annual agricultural production with daily weather outcomes to measure the effects of temperature fluctuations on total agricultural output value of farming, forestry, animal husbandry and fishing in China. We find four main results: *(i)* the total agricultural output decreases with higher spring, summer and winter temperatures and increases with higher fall temperatures; *(ii)* temperature affects agricultural output mainly through its impact on agricultural total factor productivity; *(iii)* higher temperatures increase the use of several agricultural inputs, including fertilizer, machinery, total planted acres and total irrigated acres; and *(iv)* we project that China's aggregate agricultural output will fall annually by 6.5-17.4% during the mid-21st century under the warming scenarios considered by the global climate model UKMO-HadCM3, equivalent to a monetary loss of CNY 147.6-395.0 billion in 2008 values.

Keywords: temperature, agricultural output, total factor productivity, input use

JEL Classification: Q12, Q54

1. Introduction

With global warming becoming increasingly evident, a large body of research has examined agricultural vulnerability to rising temperatures and projected how warming will shape the world's agriculture in the future. In general, the related existing studies can be divided into two strands, with the first strand focusing on assessing the impacts of rising temperatures on crop yields (for example, see Chen et al., 2016a, 2016b; Lobell et al., 2011a, 2011b; Schlenker and Roberts, 2009). These studies find that yields of major crops such as corn, soybeans, rice and wheat decline with elevated temperatures. The second strand of the literature identifies the effects of changing weather conditions on farmland values (Mendelsohn et al., 1994; Schlenker et al., 2006), which are an indicator mainly reflecting profitability from crop cultivation. Although farming accounts for a significant share in total agricultural output in many countries around the world, economic studies evaluating the impacts of rising temperatures on other agricultural sub-sectors, such as livestock, forestry and fishing, remain limited, thus limiting the ability to characterize how future warming will affect total agricultural output.

In this paper, we ask two questions. First, has temperature influenced total agricultural output value of farming, forestry, animal husbandry and fishing?¹ Second, to what extent and through which channels has temperature affected total agricultural output? Answers to these questions are far from clear. China provides an appealing setting to study these issues for at least three reasons. First, as the world's largest agricultural economy, China has experienced significant climate change over the past century, with an increase of 0.5-0.8°C in annual mean surface temperature and the distribution of rainfall between the south and the drier north becoming increasingly uneven (Ding et al., 2007). Second, although the industrial sector dominates the nation's economy, China's agricultural sector is still an important industry, as it employs over 300 million farmers and feeds over 20% of the world's population. China is a major producer of many cereal crops such as corn, wheat and rice and is the world's largest pork producer. Third, our county-level agricultural data set is unique and comprehensive. The data set used for this analysis contains detailed information on county-specific total agricultural output and major inputs used (i.e.,

*Xiaoguang Chen (corresponding author: cxg@swufe.edu.cn) and Jue Du, Southwestern University of Finance and Economics, No 55 Guanghuacun Street, Chengdu PRC.

¹ We will use total agricultural output, agricultural output, and output interchangeably in the remainder of the paper.

the total sown area, the quantity of agricultural labor, fertilizer, machinery and total irrigated acres) for approximately 2500 counties from 2001 to 2008. This allows us to explore a variety of possible channels through which temperature affects total agricultural output and to study whether Chinese farmers have undertaken adaptation strategies, such as adjusting input use, to cope with higher temperatures.

Because agricultural production in China exhibits a clear seasonal pattern, we construct temperature variables using seasonal average temperatures. To isolate the impact of temperature on agricultural output from other confounding factors, our model specification includes rainfall, sunshine hours, air pressure, relative humidity, and wind speed as additional weather variables (Zhang et al., 2017). Time-invariant county fixed effects and region \times year fixed effects are also added in the baseline model specification to minimize the estimation biases stemming from omitted variables. Our main identification strategy uses year-to-year variations in temperature to identify its effects.

We find three main results. First, our estimates show large and negative effects of higher spring, summer and winter temperatures on total agricultural output, while higher fall temperatures have the opposite effect. For each 1°C increase in the average spring, summer and winter temperatures, agricultural output falls 5.1-6.9%, 6.1-6.8% and 2.4-2.5%, respectively, depending on specifications. Output increases 4.4-5.6% for each 1°C increase in the average fall temperature.

Second, we document that temperature affects total agricultural output mainly through its impact on agricultural productivity, measured by total factor productivity (TFP). Our estimates show that the TFP-temperature relationship mirrors the output-temperature relationship. We find that, while seasonal temperature fluctuations have a limited impact on the quantity of agricultural labor, rising temperatures lead to increased use of dirty inputs, creating stress on water and air resources. The intuition is that, as productivity per unit of input decreases, farmers compensate by using a greater quantity of inputs. Specifically, we find evidence that higher spring temperatures increase total planted acres, total irrigated acres and use of agricultural machinery, while fertilizer use is positively associated with higher fall temperatures.

Third, estimated temperature impacts on agricultural output differ substantially across regions and agricultural sub-sectors. Higher spring temperatures exert large, negative impacts on agricultural output for counties located in Eastern and South Central China, while counties in North and Northwest China are most influenced by higher summer temperatures. Among the four agricultural sub-sectors considered,

forestry and animal husbandry are the two sub-sectors affected most by higher spring and summer temperatures, although the negative temperature impacts on farming and fishing are also substantial.

Taken together, our findings suggest that China's agricultural sector is still very sensitive to temperature increases, despite the substantial increases in factor inputs. We project that future warming will reduce China's aggregate agricultural output annually by 6.5-17.4% on average during the mid-21st century under the three warming scenarios considered by the global climate model UKMO-HadCM3. Given the sheer size of the Chinese agricultural economy, this is equivalent to an annual monetary loss of CNY 147.6-395.0 billion (approximately US \$20.2-54.1 billion) in 2008 values.

Only two studies have used nation-wide data to analyze the effects of temperature on national aggregate agricultural output (Dell et al., 2012; Hsiang, 2010). Using a sample of 28 Caribbean and Central American countries over the 1970-2006 period, Hsiang (2010) finds that agricultural output in these countries falls 3.9% for a 1°C increase in surface temperature during the hottest season (September, October and November in his study region), but the point estimate is statistically insignificant. By analyzing a sample of 125 counties over the 1950-2003 period, Dell et al. (2012) find that the total agricultural output in poor countries declines 2.7% for a 1°C increase in annual average temperature.

This paper makes two main contributions to the related literature. First, we provide the first nationwide estimates on the effects of temperature on total agricultural output by using a particularly rich county-level data set for the world's largest agricultural economy. As noted above, previous studies have primarily focused on estimating the impacts of higher temperatures on crop yields or farmland values. Development of national climate policies requires comprehensive estimates of the temperature effects on total agricultural output, which includes outputs not only from the crop sector but also from other sub-sectors.

Second, our findings shed light on channels by which temperature affects agricultural output and show that farmers' climate adaptation actions may have undesirable environmental impacts. By demonstrating that the effects of temperature on agricultural output mainly stem from its impacts on TFP, we provide useful information for the design of efficient strategies to alleviate the adverse impacts of higher temperatures on China's agriculture. This finding complements Liang et al. (2017), which examines the sensitivity of US agricultural TFP to seasonal temperature

variations. We add to the sparse evidence that temperature can have a direct impact on TFP, which is an essential element for agricultural economic growth. Our findings also show that rising temperatures have led Chinese farmers to increase the use of fertilizer, machinery and irrigation water, creating water and air stresses. In this regard, ours is the first paper to systematically examine the effects of temperature on total agricultural output, agricultural TFP and factor inputs.

In what follows, we present a conceptual framework in Section 2 to illustrate channels by which temperature affects agricultural output. In Section 3, we report data sources, and in Section 4, we describe our empirical strategy. In Section 5, we present results on the effects of temperature on agricultural output, and explore the impacts of temperature on agricultural TFP and input use. In Section 6, we examine heterogeneity in the effects of temperature on agricultural output. In Section 7, we project the impacts of future warming. Finally, Section 8 concludes.

2. Conceptual Framework

In this section, we develop a simple conceptual framework to illustrate possible channels by which temperature affects agricultural output. Consider a representative farmer who uses inputs x_i with $i \in \{1, 2, \dots, N\}$ for agricultural production. For simplicity, we assume that this farmer produces a single product (Y). Then, the farmer's production function can be expressed as:

$$Y = A \prod_{i=1}^N x_i^{\alpha_i} \quad (1)$$

Here, A refers to this farmer's TFP. This farmer uses a variety of inputs for agricultural production. Among others, these inputs may include land, labor, machinery, fertilizer, pesticides, and water for irrigation. TFP measures the average of these input productivities, weighted by the output elasticities of each input, denoted by α_i .

From Equation (1), we note that temperature affects agricultural output through several possible channels. Effects of temperature on labor productivity have been well documented. By causing discomfort, fatigue, and pain, high temperatures can adversely affect labor productivity (González-Alonso et al., 1999; Zivin and Neidell, 2014). Temperature also affects machine performance (Mostafavi and Agnew, 1996). Hence, temperature variations are expected to affect not only agricultural TFP, but also labor employment in agriculture.

Changes in temperature are expected to affect the quantities of other inputs that farmers use. To mitigate the adverse impacts of high temperatures on agriculture, farmers may undertake a variety of adaptive management strategies by making adjustments in input use. Prior studies have discovered that pests and diseases become more abundant and are likely to expand their geographic ranges with higher temperatures (Cannon, 1998; Piao et al., 2010). Higher temperatures may also cause sizeable losses of nitrogen and soil moisture in agricultural and forest regions. These temperature-induced stresses on crops and forest products may lead to increased fertilizer and chemical use (Porter et al., 1995; Reidsma et al., 2010). To mitigate heat stress impacts on crop, livestock and fishery production, the demand for water is also expected to rise with higher temperatures (Adams et al., 1990; Thornton et al., 2009). Moreover, adaptation to warmer climates may involve expanding the area used for crop cultivation and increasing the use of agricultural machinery to improve efficiency.

Our first objective is to examine whether temperature has any remaining effects on total agricultural output, net of all potential adaptations and adjustments in input use. We will then investigate through which channels temperature affects output.

3. Data

3.1 Agricultural Data

We collect county-level information on agricultural outputs and inputs in mainland China for years 2001-2008 from the *National Bureau of Statistics of China (NBS)*.² We measure a county's total agricultural output using the deflated gross value of agricultural output (in billion CNY), which is the sum of the total value of outputs from farming, forestry, animal husbandry and fisheries. The data set contains five major categories of agricultural inputs, including labor (in thousand persons), fertilizer (in thousand tons), machinery (in thousand kilowatts), total irrigated acreage (in thousand hectares) and total planted acreage (in thousand hectares). Fertilizer denotes the actual utilization of nitrogen, phosphate, potash and compound fertilizers in agriculture. Machinery refers to the total mechanical power of agricultural machinery used for production. The *NBS* also reports the total irrigated and planted acres for each county.

² The *NBS* also releases county-level agricultural data for years other than 2001-2008. However, the data sets in those years have incomplete information on input use, which is essential for agricultural TFP calculation. Hence, our analysis only uses the agricultural data from 2001 to 2008.

Several estimation methods have been developed to estimate agricultural TFP growth (for a detailed review, see Wu, 2011). In contrast to the parametric approach used in early studies (for example, see Fan and Pardey, 1997; Lin, 1992; McMillan et al., 1989), the Malmquist index approach based on the nonparametric method has gained great popularity in recent years (Wu, 2011). Unlike the parametric approach, the calculation of the Malmquist index neither requires price information nor makes behavioral assumptions, and can decompose TFP changes into technical changes and efficiency changes (Chen et al., 2008). Thus, we use the Malmquist index to compute agricultural TFP changes (TFPC) from the previous year over the sample period.

We exclude observations from the original sample if (i) key output and input variables mentioned above have missing or unreasonable values, and (ii) a county's computed TFPC is either below the 1.0% level or above the 99.0% level, to ensure that our regression results are not biased due to mis-specified observations.

3.2 Weather Data

We collect daily weather data from the China Meteorological Data Sharing Service System, which reports daily weather outcomes, including average temperature, rainfall, sunshine hours, air pressure, relative humidity, and wind speed, for 820 weather stations in mainland China. The data set also contains latitudes and longitudes of each weather station, enabling us to merge the weather data with our county-level agricultural data. For counties with more than one weather station, the simple average of the weather variables across weather stations is used to construct county-level weather variables. For counties without a weather station, we construct weather variables based on weather outcomes in their respective nearest neighboring counties.

Because we use TFPC as the indicator of agricultural productivity growth, we lose the observations in 2001. The final data set used for our empirical analyses contains 10,972 observations for years 2002-2008. Table 1 reports the summary statistics of the agricultural and weather variables. We find that the sample mean of the total agricultural output is 1.65 billion CNY, while the average size of the labor force in agriculture is 138.5 thousand. The average TFPC of 1.2 during the 2002-2008 period was remarkable. Other input and weather variables also exhibited considerable variability during the sample period. Table 1 also reveals that, in most Chinese counties included in the sample, farming and animal husbandry are the two major subsectors contributing to the total agricultural output.

4. Empirical Strategy

We use the following model specification to examine the effects of temperature on agricultural production:

$$\log Y_{i,t} = \beta_0 T_{i,t} + \beta_1 W_{i,t} + \gamma \theta_{i,t} + c_i + \varepsilon_{i,t} \quad (2)$$

where $Y_{i,t}$ denotes the total agricultural output in county i in year t . $T_{i,t}$ denotes seasonal average temperature variables, including average spring, summer, fall and winter temperatures, denoted by $\text{Temp}^{\text{spring}}$, $\text{Temp}^{\text{summer}}$, $\text{Temp}^{\text{fall}}$ and $\text{Temp}^{\text{winter}}$, respectively. Most regions in China have clear distinctions of four seasons. Following the tradition of agricultural production activity in China, we define the spring as March through May, the summer as June through August, the fall as September through November, and the winter as December through February. To isolate the effect of temperature from other confounding factors, we include a comprehensive set of weather variables. In addition to temperature, we include sums of rainfall and sunshine hours and means of air pressure, relative humidity, and average wind speed for each season. $W_{i,t}$ is a vector containing these weather variables. $\theta_{i,t}$ denotes region \times year fixed effects, accounting for common shocks occurring in a region in a given year that had the same effects on agricultural production for all counties in that region in that year, such as trends in climate or regional-specific agricultural policies. c_i denotes county fixed effects. Lastly, $\varepsilon_{i,t}$ are the error terms.

β_0 is the key parameter of interest and measures the percentage changes in agricultural output with a one-unit increase in temperature variables. The effects of temperature on agricultural output are identified from the random variations in temperature over time. We control for the heteroskedasticity of the error terms and allow the error terms $\varepsilon_{i,t}$ to be both spatially and serially correlated by clustering standard errors in two dimensions: within counties and within (prefecture-level) city-years (Cameron et al., 2011). The former accounts for autocorrelation within each county, while the latter accounts for spatial correlation across contemporary counties within each prefectural city.

5. Effects of Temperature on Agricultural Output

The main focus of this paper is to examine the effects of temperature on agricultural output. For brevity, we only report parameter estimates of temperature variables in Table 2 and do not report parameter estimates of other weather variables.

5.1 Baseline Results

Column 1 of Table 2 shows our baseline results. We find that the coefficient estimates of the $\text{Temp}^{\text{spring}}$, $\text{Temp}^{\text{summer}}$ and $\text{Temp}^{\text{winter}}$ variables are negative and statistically significant at the 1% level, indicating that agricultural output is negatively correlated with higher spring, summer and winter temperatures. Specifically, holding all else the same, a 1°C increase in average spring temperature is associated with a reduction of 5.1% in agricultural output, while a 1°C increase in average winter temperature can reduce agricultural output by 2.4%. Relative to the negative impacts of higher spring and winter temperatures, the reduction in the total agricultural output stemming from elevated summer temperatures is significantly larger. Holding all else constant, a 1°C increase in average summer temperature is associated with a reduction of 6.8% in output.

The vast majority of cropping activities in China occurs in spring. Hotter springs can lead to losses of soil moisture and soil organic matter (Kirschbaum, 1995), reducing the availability of moisture and organic matter for the subsequent crop growing seasons. It has been well documented that higher summer temperatures have detrimental impacts on crop yields (Chen et al., 2016b, 2016a; Lobell et al., 2011a; Schlenker and Roberts, 2009). Hot summers can also negatively affect the production of forest products (i.e., wood products, mushrooms, edible nuts, fruits and others) and increase the production costs of confined animal operations (i.e., hogs, cattle, chickens, and fish). Moreover, higher temperatures in spring and summer months may increase irrigation needs, which increases the mechanical power used for agricultural production and consequently lowers the total agricultural output. Cold winter can kill many damaging insects and diseases. Thus, when winter becomes warmer, pests may become more prevalent, which creates pest problems during crop growing seasons.

The parameter estimate of the $\text{Temp}^{\text{fall}}$ variable is positive and statistically significant at the 1% level, suggesting that agricultural output increases with higher fall temperatures. Holding all else equal, a 1°C increase in average fall temperature is associated with an increase of 5.6% in agricultural output. Agricultural output benefits from warmer fall months, possibly because higher fall temperatures allow crops to achieve full maturity, while facilitating crop harvest (Liang et al., 2017).

Although there exist differing impacts of temperature across seasons, the sum of the effects of seasonal temperature variations on total agricultural output remains substantially negative. For a 1°C increase in average temperatures in all seasons, the total agricultural output declines 8.7%. These findings remain broadly consistent

when we incorporate one-year lagged values of the weather variables as additional explanatory variables. We also find that the total agricultural output exhibits low levels of responsiveness to temperature variations in the previous year (see Table A1 in the appendix), which are expected given that agricultural output is more likely to be affected by contemporaneous temperature changes rather than lagged temperature changes.

5.2 Robustness Checks

We conduct several robustness checks to probe the sensitivity of our findings to variations in model specifications and data. Our baseline specification incorporates region \times year fixed effects to capture the shocks occurring in a region in a given year that may have the same effects on agricultural output for all counties located in that region in that year. Here, we consider two alternative specifications, with province \times year fixed effects in Scenario (1) and (prefecture-level) city \times year fixed effects in Scenario (2). We consider these two specifications mainly due to the concern that individual provinces (or prefecture-level cities) may have implemented specific agricultural policies during the sample period to boost the rural economy. These policies are not directly observable in our data but may have affected agricultural output in counties located in that province (or city). In Scenario (3), we replicate the above analyses by removing observations if a county's computed TFPC is either below 2.5% or above 97.5% (rather than below the 1.0% level or above the 99.0% level in the baseline analysis) to further ensure that our results are not affected by potentially mis-specified outliers.

Columns 2-4 of Table 2 report coefficient estimates of temperature variables for the three scenarios. We find that our key findings presented in the baseline scenario remain robust. The negative effect on agricultural output stemming from rising $\text{Temp}^{\text{spring}}$ ranges between 5.5% and 6.9%. The effect on agricultural output of each 1°C increase in $\text{Temp}^{\text{summer}}$ is found to be 6.1-6.2% across the three scenarios. The positive effect of 1°C higher $\text{Temp}^{\text{fall}}$ on agricultural output ranges between 4.4% and 5.5%. The estimated effects of $\text{Temp}^{\text{winter}}$ on agricultural output are also remarkably consistent with our baseline estimate, which is -2.5% for each 1°C increase in average winter temperature. The sum of the effects of rising seasonal temperatures on the total agricultural output is found to be (-) 8.5-11.1% across these scenarios, which is also similar to our baseline estimate (-8.7%).

To put these results in context, we compare our point estimates with prior studies. Hsiang (2010) finds that, in Caribbean and Central American countries, agricultural

output declined 3.9% for a 1°C increase in surface temperature during the hottest season over the 1970-2006 period. Dell et al. (2012) find that agricultural output in poor countries fell 2.7% for each 1°C increase in annual average temperature during the 1950-2003 period. Our estimates of the negative effect of higher temperatures on China's agricultural output are significantly larger than these prior estimates, suggesting that China's agriculture is highly vulnerable to global warming.

5.3 Temperature Effects on Agricultural Productivity and Input Use

Based on the conceptual insights presented in Section 2, here we investigate potential channels through which temperature affects agricultural output, using the same model specification as in Equation (2). Table 3 shows the estimated temperature effects on several key components of agricultural production, namely TFPC; quantities of labor, fertilizer, and machinery; total planted acres; and total irrigated acres. In the regression analyses, we take the natural logs for these variables, with an exception for the TFPC variable. These estimated temperature effects are thus interpreted as the percentage changes in these variables with a 1°C increase in temperature.

Column 1 of Table 3 shows that the TFPC-temperature relationship is almost identical to the agricultural output-temperature relationship, though the point estimates differ to some extent. TFPC is negatively correlated with elevated $\text{Temp}^{\text{spring}}$ and $\text{Temp}^{\text{summer}}$, and positively correlated with higher $\text{Temp}^{\text{fall}}$. Specifically, holding all else constant, for each 1°C increase in $\text{Temp}^{\text{spring}}$ and $\text{Temp}^{\text{summer}}$, TFPC declines 8.7% and 6.1%, respectively. A 1°C higher $\text{Temp}^{\text{fall}}$ is associated with 3.1% higher agricultural productivity, whereas the effect of $\text{Temp}^{\text{winter}}$ on TFPC is insignificant. These findings are in line with those reported in Liang et al. (2017).

Column 2 of Table 3 shows that the quantity of labor exhibits a negative response to higher $\text{Temp}^{\text{winter}}$ and is not responsive to temperature changes in the other three seasons. Specifically, a 1°C higher $\text{Temp}^{\text{winter}}$ reduces the amount of labor employed in agriculture by 0.4%. That is the case, possibly, because when winter becomes warmer, it lowers farmers' expectations for returns from subsequent production, resulting in reduced labor input for agricultural production. Column 3 shows that fertilizer use increases with higher $\text{Temp}^{\text{fall}}$. One possible explanation for this finding is that, although higher $\text{Temp}^{\text{fall}}$ facilitates harvest, it may decrease soil organic matter, creating an increased demand for fertilizer.

Columns 4-6 report positive and significant impacts of higher $\text{Temp}^{\text{spring}}$ on agricultural machinery use, total planted acres and total irrigated acres. These results suggest that, to reduce the negative effects of higher $\text{Temp}^{\text{spring}}$ on agricultural output, Chinese farmers have increased their use of agricultural machinery, total planted acres and irrigated acres for agricultural production. Holding all else the same, a 1°C increase in $\text{Temp}^{\text{spring}}$ increases machinery use, total planted acres and total irrigation acres by 1.6%, 3.1% and 3.1%, respectively. Temperature changes in summer, fall and winter have no effects on the quantity used of these three inputs. These findings remain broadly consistent if we use model specifications and data considered in the robustness check section (see Figure 1).

6. Heterogeneous Temperature Effects

The estimated effects of temperature on agricultural output, TFPC and input use may differ across regions and agricultural sub-sectors due to regional differences in exposure to high temperatures and sensitivities of agricultural sub-sectors to high temperatures. This section explores the heterogeneity in temperature effects.

6.1 Heterogeneity Across Regions

Figure 2 displays the temperature effects on agricultural output across regions (Appendix A lists the provinces included in each of the six traditional agricultural regions in China). For brevity, we only present the parameter estimates of the $\text{Temp}^{\text{spring}}$ and $\text{Temp}^{\text{summer}}$ variables in Figure 2, because higher spring and summer temperatures have large and negative effects on output and their magnitudes are considerably larger than the negative impact due to higher winter temperatures.

We find substantial differences in estimated temperature impacts across regions. Counties located in Eastern and South Central China are most affected by higher spring temperatures. Holding all else equal, the total agricultural output in the two regions declines 10.6% and 8.9%, respectively, for each 1°C increase in $\text{Temp}^{\text{spring}}$. The negative output- $\text{Temp}^{\text{spring}}$ relationship in the two regions mainly stems from the negative effects of higher spring temperatures on TFPC. Our regression results indicate that a 1°C increase in $\text{Temp}^{\text{spring}}$ is associated with reductions of 9.9% and 27.4% in TFPC in Eastern and South Central China, respectively. To mitigate the adverse impacts of higher $\text{Temp}^{\text{spring}}$ on agricultural output, farmers in Eastern China have increased fertilizer use, total planted acres and total irrigated acres by 3.9%, 8.3% and 6.3%, respectively, for each 1°C increase in $\text{Temp}^{\text{spring}}$. In contrast, farmers in South Central China reduce the negative impact of higher $\text{Temp}^{\text{spring}}$ mainly by

increasing labor used in agriculture. Holding all else constant, a 1°C higher Temp^{spring} is associated with 1.6% higher use of agricultural labor in South Central China.

Higher Temp^{summer} exerted significant negative impacts on agricultural production for counties located in North and Northwest China. We find that a 1°C higher Temp^{summer} is associated with 13.1% and 15.2% lower agricultural output in North and Northwest China, respectively. Consistent with our baseline results based on the full sample, the negative output-Temp^{summer} relationship in the two regions is mainly driven by the negative responses of TFPC to higher Temp^{summer}. Our results indicate that a 1°C increase in Temp^{summer} is associated with reductions of 23.5% and 16.0% in TFPC in North and Northwest China, respectively. The result on labor suggests that higher Temp^{summer} reduces agricultural labor by 5.0% in Northwest China. The responses of other inputs including fertilizer, machinery, total planted acres and total irrigated acres in the two regions to Temp^{summer} changes are insignificant.

6.2 Heterogeneity Across Agricultural Sub-Sectors

We estimate Equation (2) for each of the four agricultural sub-sectors to examine which sub-sectors are most affected by temperature variations. Table 4 reports our regression results. We find that, although all four sub-sectors exhibit strong negative responses to changes in Temp^{spring} and Temp^{summer}, forestry and animal husbandry are the two sub-sectors hit most by higher spring and summer temperatures. Columns 2 and 3 of Table 4 show that the effects of a 1°C increase in Temp^{spring} are output reductions of 6.9% and 8.0%, respectively, in the two sub-sectors. In comparison, output reductions in the farming and fishery sectors are smaller, at 5.8% and 5.7%, respectively. The negative impacts of higher Temp^{summer} on the forestry and animal husbandry sectors are also substantial. For each 1°C increase in Temp^{summer}, the total agricultural output in the two sub-sectors declines 10.8% and 7.4%, respectively, whereas the output reductions are 6.0% in the farming sector and 4.1% in the fishery sector.

The differences in the agricultural sub-sectors' sensitivities to temperature may partly explain why estimated temperature impacts differ across regions. Table 1 shows that animal husbandry is a major agricultural sub-sector in China, accounting for approximately 34% of the total agricultural output, while the fishery sector only contributes 5.7% to the total agricultural output. Thus, in exploring the heterogeneity in temperature effects, we focus our attention on regional differences in the levels of output from animal husbandry.

To mitigate the adverse impacts of high temperatures on crop production, farmers can take a variety of adaptation measures, by diversifying crop production, adjusting production practices, or altering planting and harvest dates (Howden et al., 2007). Unlike crop farmers, livestock farmers may have limited options to cope with higher temperatures, because most livestock production in China occurs in industrialized farms and adaptations can be very costly. Thus, regions that heavily rely on livestock production are likely to be hit harder by elevated temperatures than other regions.

To test this conjecture, we modify Equation (2) by adding one new set of variables, which are the interaction terms between weather variables and a “large-livestock” dummy. We define a county as a large-livestock production region if the average share of the output from livestock production in the total agricultural output over the sample period is equal to or above 50%. For the reason mentioned above, we only report coefficient estimates of $\text{Temp}^{\text{spring}}$ and $\text{Temp}^{\text{summer}}$ in Table 5.

The result for total agricultural output, shown in Column 1 of Table 5, shows that the parameter estimate of the interaction term between the “large-livestock” dummy and $\text{Temp}^{\text{summer}}$ is negative and statistically significant at the 5% level. This suggests that, relative to small-livestock production regions, elevated summer temperatures have a larger negative impact on total agricultural output in large-livestock production regions. Specifically, holding all else constant, a 1°C higher $\text{Temp}^{\text{summer}}$ is associated with 10.6% lower output in large-livestock production regions, and this negative impact is 4.7% larger than that in small-livestock production regions.

Column 2 of Table 5 indicates that this large, negative impact on agricultural output in large-livestock production regions is mainly driven by the negative response of TFPC to higher $\text{Temp}^{\text{summer}}$. The parameter estimate of the interaction term between the “large-livestock” dummy and $\text{Temp}^{\text{summer}}$ is negative and statistically significant at the 1% level. This result suggests that, compared to small-livestock production regions, a 1°C increase in $\text{Temp}^{\text{summer}}$ leads to an additional 9.8% reduction in TFPC in large-livestock production regions. The interaction terms between the “large-livestock” dummy and $\text{Temp}^{\text{summer}}$ for factor inputs are either insignificant or exhibit low levels of statistical significance.

The interaction terms between $\text{Temp}^{\text{spring}}$ and the “large-livestock” dummy are insignificant in Columns 1 and 2, suggesting that the responses of agricultural output and TFPC in large- and small-livestock production regions to $\text{Temp}^{\text{spring}}$ changes are not significantly different. Regression results in Columns 3-7 suggest that higher spring temperatures lead to increased labor use in large-livestock regions, relative to

small-livestock regions, offsetting the negative Temp^{spring} impacts on agricultural machinery, total planted acres and total irrigated acres.

7. Impacts of Future Warming

This section quantifies the potential impact of future warming on the total agricultural output in China. Projections of future climate variables are taken from ClimateWizard (<http://www.climatewizard.org/>), which provides monthly average temperature and total precipitation for Mid Century (2050s) and End Century (2080s). Future climate variables are provided under three emissions scenarios: the low B1, the medium A1B and the high A2 scenarios, based on the most recent global climate models. We take the climate projections under the three emissions scenarios using the widely-used global climate model UKMO-HadCM3 and download the data at 50 km spatial resolution, which enables us to obtain future climate variables for all counties included in our sample.

When projecting the impact of future warming on national agricultural output, we first calculate county-specific changes in seasonal average temperatures, based on the ClimateWizard database and the sample seasonal mean temperatures. The projected changes in seasonal average temperatures are then multiplied by parameter estimates of the seasonal average temperature variables reported in Table 2 to compute predicted changes in the total agricultural output for all counties, weighted by their shares in the national aggregate agricultural output over the sample period. We focus on the Mid Century's impacts only, because our parameter estimates of the temperature variables based on short-term observations cannot capture the potential adaptations undertaken by farmers in the long term to cope with future warming.

Table 6 shows that China's aggregate agricultural output is projected to decline annually by 6.5-7.5% under the B1 scenario, 14.9-17.4% under the A1B scenario, and 9.3-11.0% under the A2 scenario during the mid-21st century. The sample mean aggregate agricultural output over our study period was CNY 2.27 trillion in 2008 prices. These projected output losses due to future warming are, therefore, equivalent to CNY 147.6-170.3 billion annually under the B1 scenario, CNY 338.2-395.0 billion under the A1B scenario, and CNY 211.1-249.7 billion under the A2 scenario.

Table 7 shows that the primary cause of future output losses is the projected reduction in TFPC, which is projected to decline 9.0-16.5% across the three warming scenarios by 2050. Fertilizer use, machinery use, total planted acres and total irrigated

acres are projected to increase 1.3-2.7%, 0.5-1.6%, 2.8-6.5%, and 1.3-3.6%, respectively, by 2050. The impact of future warming on labor is projected to be small.

8. Conclusions and Discussion

This paper provides the first comprehensive county-level analysis that not only assesses the effects of temperature on China's national agricultural output, but also explores channels by which temperature affects output. We find that agricultural output exhibits different responses to seasonal temperature changes. Our preferred model estimates show that agricultural output falls 5.1%, 6.8% and 2.4%, respectively, for each 1°C increase in average spring, summer and winter temperatures, and increases 5.6% for each 1°C increase in average fall temperatures. These estimates remain robust to a number of variations in model specifications and data.

Our further investigation finds that the relationship between agricultural total factor productivity change (TFPC) and temperature is almost identical to the output-temperature relationship. This result suggests that, when developing climate adaptation policies to mitigate the adverse impacts of higher temperatures on China's agriculture, one should prioritize strategies to minimize the negative impacts of higher temperatures on agricultural productivity. Higher temperatures have also caused Chinese farmers to increase the use of several agricultural inputs, including fertilizer, machinery, land, and irrigation water, which may generate undesirable environmental impacts.

We find substantial heterogeneity in the effects of temperature on agricultural output. Cooler springs in Eastern and South Central China would be more productive, whereas North and Northwest China would benefit from cooler summers. Forestry and animal husbandry are the two sub-sectors most affected by higher spring and summer temperatures, although the negative temperature impacts on the farming and fishery sectors are also considerable.

Taken together, these findings suggest that China's agricultural sector is still very sensitive to rising temperatures, in spite of the significant increases in input use. China's aggregate agricultural output is projected to decline annually by 6.5-17.4% (or CNY 147.6-395.0 billion in 2008 values) during the mid-21st century under the three warming scenarios considered by the global climate model UKMO-HadCM3.

The primary caveat of this work is that our data set spans a short period of time. In the long run, farmers may take a variety of adaptation measures to cope with future

warming, and these climate adaptations cannot be incorporated when projecting the future output losses. As a result, we may have over-stated the climate impact on China's agriculture relative to the actual damages that will occur.

References

- Adams, R.M., Rosenzweig, C., Peart, R.M., Ritchie, J.T., McCarl, B.A., Glycer, J.D., Curry, R.B., Jones, J.W., Boote, K.J., Allen, L.H., 1990. Global climate change and US agriculture. *Nature*. doi:10.1038/345219a0
- Cameron, A.C., Gelbach, J.B., Miller, D.L., 2011. Robust Inference With Multiway Clustering. *J. Bus. Econ. Stat.* 29, 238–249. doi:10.1198/jbes.2010.07136
- Cannon, R.J.C., 1998. The implications of predicted climate change for insect pests in the UK, with emphasis on non-indigenous species. *Glob. Chang. Biol.* doi:10.1046/j.1365-2486.1998.00190.x
- Chen, P.C., Yu, M.M., Chang, C.C., Hsu, S.H., 2008. Total factor productivity growth in China's agricultural sector. *China Econ. Rev.* doi:10.1016/j.chieco.2008.07.001
- Chen, S., Chen, X., Xu, J., 2016a. Assessing the impacts of temperature variations on rice yield in China. *Clim. Change* 138. doi:10.1007/s10584-016-1707-0
- Chen, S., Chen, X., Xu, J., 2016b. Impacts of climate change on agriculture: Evidence from China. *J. Environ. Econ. Manage.* 76, 105–124. doi:10.1016/j.jeem.2015.01.005
- Dell, M., Jones, B.F., Olken, B.A., 2012. Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *Am. Econ. J. Macroecon.* 4, 66–95. doi:10.1257/mac.4.3.66
- Ding, Y., Ren, G., Zhao, Z., Xu, Y., Luo, Y., Li, Q., Zhang, J., 2007. Detection, causes and projection of climate change over China: An overview of recent progress, in: *Advances in Atmospheric Sciences*. pp. 954–971. doi:10.1007/s00376-007-0954-4
- Fan, S., Pardey, P.G., 1997. Research, productivity, and output growth in Chinese agriculture. *J. Dev. Econ.* 53, 115–137. doi:https://doi.org/10.1016/S0304-3878(97)00005-9
- González-Alonso, J., Teller, C., Andersen, S.L., Jensen, F.B., Hyldig, T., Nielsen, B., 1999. Influence of body temperature on the development of fatigue during prolonged exercise in the heat. *J. Appl. Physiol.* 86, 1032–1039.

- Howden, S.M., Soussana, J.-F., Tubiello, F.N., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. *Proc. Natl. Acad. Sci.* 104, 19691 LP-19696. doi:10.1073/pnas.0701890104
- Hsiang, S.M., 2010. Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proc. Natl. Acad. Sci. U. S. A.* 107, 15367–72. doi:10.1073/pnas.1009510107
- Kirschbaum, M.U.F., 1995. The temperature dependence of soil organic matter decomposition, and the effect of global warming on soil organic C storage. *Soil Biol. Biochem.* doi:10.1016/0038-0717(94)00242-S
- Liang, X.-Z., Wu, Y., Chambers, R.G., Schmoltdt, D.L., Gao, W., Liu, C., Liu, Y.-A., Sun, C., Kennedy, J.A., 2017. Determining climate effects on US total agricultural productivity. *Proc. Natl. Acad. Sci.* doi:10.1073/pnas.1615922114
- Lin, J.Y., 1992. Rural reforms and agricultural growth in China. *Am. Econ. Rev.* doi:10.2307/2117601
- Lobell, D.B., Bänziger, M., Magorokosho, C., Vivek, B., 2011a. Nonlinear heat effects on African maize as evidenced by historical yield trials. *Nat. Clim. Chang.* 1, 42–45. doi:10.1038/nclimate1043
- Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011b. Climate Trends and Global Crop Production Since 1980. *Science* (80-.). 333, 616–620.
- McMillan, J., Whalley, J., Zhu, L., 1989. The impact of China's economic reforms on agricultural productivity growth. *J. Polit. Econ.* doi:10.1086/261628
- Mendelsohn, R., Nordhaus, W.D., Shaw, D., 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis. *Am. Econ. Rev.* 84, 753–771.
- Mostafavi, M., Agnew, B., 1996. The impact of ambient temperature on lithium-bromide/water absorption machine performance. *Appl. Therm. Eng.* 16, 515–522. doi:10.1016/1359-4311(95)00004-6
- Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., Zhou, L., Liu, H., Ma, Y., Ding, Y., Friedlingstein, P., Liu, C., Tan, K., Yu, Y., Zhang, T., Fang, J., 2010. The impacts of climate change on water resources and agriculture in China. *Nature* 467, 43–51. doi:10.1038/nature09364
- Porter, J.R., Leigh, R.A., Semenov, M.A., Miglietta, F., 1995. Modelling the effects of climatic change and genetic modification on nitrogen use by wheat. *Eur. J. Agron.* 4, 419–429. doi:https://doi.org/10.1016/S1161-0301(14)80094-4

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- Reidsma, P., Ewert, F., Lansink, A.O., Leemans, R., 2010. Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses. *Eur. J. Agron.* doi:10.1016/j.eja.2009.06.003
- Schlenker, W., Hanemann, W., Fisher, A., 2006. The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. *Rev. Econ. Stat.* 88, 113–125.
- Schlenker, W., Roberts, M.J., 2009. Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proc. Natl. Acad. Sci.* 106, 15594–15598. doi:10.1073/pnas.0906865106
- Thornton, P.K., van de Steeg, J., Notenbaert, A., Herrero, M., 2009. The impacts of climate change on livestock and livestock systems in developing countries: A review of what we know and what we need to know. *Agric. Syst.* doi:10.1016/j.agsy.2009.05.002
- Wu, Y., 2011. Total factor productivity growth in China: a review. *J. Chinese Econ. Bus. Stud.* 9, 111–126. doi:10.1080/14765284.2011.568682
- Zhang, P., Zhang, J., Chen, M., 2017. Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. *J. Environ. Econ. Manage.* 83, 8–31. doi:10.1016/j.jeem.2016.12.001
- Zivin, J.G., Neidell, M., 2014. Temperature and the Allocation of Time: Implications for Climate Change. *J. Labor Econ.* 32, 1–26. doi:10.1086/671766

Table 1. Summary Statistics

Variable	Unit	Mean	Std. Dev.	Min	Max
Panel A: Agricultural data					
Agricultural output	billion CNY	1.653	1.522	0.009	12.280
TFPC	-	1.210	0.362	0.394	3.069
Labor	thousand persons	138.498	102.770	0.383	953.410
Machinery	thousand kilowatts	305.409	326.572	0.734	3,902.011
Fertilizer	thousand tons	22.072	24.084	0.003	668.119
Total irrigated acres	thousand hectares	24.941	27.017	0.020	885.240
Total planted acres	thousand hectares	72.985	63.992	0.000	1,245.704
% of output from farming	%	52.3	13.8	0.0	100.0
% of output from forestry	%	5.7	7.1	0.0	84.9
% of output from animal husbandry	%	34.1	14.0	0.0	95.2
% of output from fishing	%	6.1	11.2	0.0	99.6
Panel B: Weather data					
Temp ^{spring}	°C	14.686	4.833	-2.826	27.675
Temp ^{summer}	°C	24.281	3.845	6.496	30.184
Temp ^{fall}	°C	14.638	5.509	-5.524	27.636
Temp ^{winter}	°C	2.219	7.985	-26.752	23.568
Rain ^{spring}	cm	22.816	18.705	0.000	112.240
Rain ^{summer}	cm	44.519	23.267	0.260	213.330
Rain ^{fall}	cm	16.823	12.211	0.000	134.890
Rain ^{winter}	cm	7.696	8.413	0.000	46.890
Sunshine ^{spring}	hour	549.848	180.431	0.000	1,002.600
Sunshine ^{summer}	hour	558.810	144.754	0.000	1,103.800
Sunshine ^{fall}	hour	484.556	144.905	0.000	908.100
Sunshine ^{winter}	hour	404.802	170.615	24.400	864.200
Air pressure ^{spring}	hPa	946.333	85.753	587.280	1,016.534
Air pressure ^{summer}	hPa	940.121	83.033	589.463	1,006.627
Air pressure ^{fall}	hPa	950.882	85.912	590.344	1,020.774
Air pressure ^{winter}	hPa	955.136	89.349	583.988	1,029.036
Humidity ^{spring}	%	63.037	14.152	19.609	90.620
Humidity ^{summer}	%	73.292	9.515	22.761	93.913
Humidity ^{fall}	%	70.691	9.835	27.923	92.714
Humidity ^{winter}	%	67.025	11.798	14.667	90.714
Wind speed ^{spring}	m/s	2.334	0.977	0.364	11.307
Wind speed ^{summer}	m/s	1.941	0.817	0.291	11.615
Wind speed ^{fall}	m/s	1.821	0.835	0.247	8.420
Wind speed ^{winter}	m/s	1.940	0.899	0.163	7.979

Notes: This table shows summary statistics on our key variables of interest over the period 2002-2008. Unit of observation is a county-year. Number of observations is 10,972.

Table 2. Effects of Temperature on Agricultural Output

	Baseline	Scenario (1)	Scenario (2)	Scenario (3)
	Region \times year fixed effects	Province \times year fixed effects	City \times year fixed effects	Dropping observations if TFPC is below the 2.5% or above the 97.5% level
	(1)	(2)	(3)	(4)
Temp ^{spring}	-0.051*** (0.008)	-0.065*** (0.008)	-0.069*** (0.008)	-0.055*** (0.007)
Temp ^{summer}	-0.068*** (0.012)	-0.062*** (0.011)	-0.061*** (0.010)	-0.061*** (0.011)
Temp ^{fall}	0.056*** (0.010)	0.048*** (0.010)	0.044*** (0.009)	0.055*** (0.010)
Temp ^{winter}	-0.024*** (0.004)	-0.025*** (0.004)	-0.025*** (0.004)	-0.025*** (0.004)
Sum of all temperature variable coefficients	-0.087*** (0.016)	-0.105*** (0.015)	-0.111*** (0.013)	-0.085*** (0.015)
Observations	10,972	10,972	10,972	10,634
R^2	0.969	0.971	0.976	0.971

Notes: This table shows temperature effects on agricultural output in the baseline scenario and the three scenarios considered in the robustness check section. Column 1 shows the baseline results with region \times year fixed effects. Column 2 shows the regression results with province \times year fixed effects. Column 3 shows the regression results with city \times year fixed effects. Column 4 shows the regression results by removing observations if a county's computed TFPC is either below the 2.5% level or above the 97.5% level (rather than below the 1.0% level or above the 99.0% level in the baseline analysis). These estimated temperature effects can be interpreted as the percentage changes in output with a 1°C increase in temperature. Sunshine hours, rainfall, air pressure, relative humidity, and average wind speed are included as additional weather variables. Standard errors, shown in parentheses, are clustered within counties and within prefecture-level city-years. Units for explanatory variables: 1°C for temperature. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3. Temperature Effects on Agricultural Productivity and Input Use

	TFPC	Labor	Fertilizer	Machinery	Total planted acres	Total irrigated acres
	(1)	(2)	(3)	(4)	(5)	(6)
Temp ^{spring}	-0.087*** (0.013)	-0.007 (0.004)	0.004 (0.008)	0.016** (0.007)	0.031*** (0.012)	0.031** (0.013)
Temp ^{summer}	-0.061*** (0.018)	0.006 (0.006)	-0.008 (0.010)	-0.006 (0.009)	0.001 (0.006)	-0.013 (0.013)
Temp ^{fall}	0.031** (0.013)	-0.001 (0.004)	0.018** (0.008)	0.006 (0.007)	0.008 (0.005)	0.014 (0.009)
Temp ^{winter}	0.006 (0.007)	-0.004** (0.002)	0.006* (0.003)	0.001 (0.004)	0.004 (0.002)	0.004 (0.004)
Sum of all temperature coefficients	-0.111*** (0.022)	-0.006 (0.008)	0.021 (0.015)	0.017 (0.011)	0.043*** (0.017)	0.035 (0.022)
Observations	10,972	10,972	10,972	10,972	10,971	10,972
R ²	0.286	0.982	0.972	0.954	0.971	0.947

Notes: This table shows the estimated temperature effects on several key components of agricultural production, including TFPC; quantities of labor, fertilizer, machinery; total planted acres; and total irrigated acres. We take the natural logs for these variables, with an exception for the TFPC variable. These estimated temperature effects can be interpreted as the percentage changes in these variables with a 1°C increase in temperature. Sunshine hours, rainfall, air pressure, relative humidity, and average wind speed are included as additional weather variables. Standard errors, shown in parentheses, are clustered within counties and within prefecture-level city-years. Units for explanatory variables: 1°C for temperature. ***p<0.01, ** p<0.05, *p<0.1

Table 4. Effects of Temperature on Agricultural Sub-Sectors' Output

	Farming	Forestry	Animal husbandry	Fishing
	(1)	(2)	(3)	(4)
Temp ^{spring}	-0.058*** (0.011)	-0.069*** (0.015)	-0.080*** (0.009)	-0.057*** (0.012)
Temp ^{summer}	-0.060*** (0.013)	-0.108*** (0.020)	-0.074*** (0.013)	-0.041** (0.020)
Temp ^{fall}	0.033** (0.015)	0.057*** (0.016)	0.052*** (0.011)	0.030** (0.014)
Temp ^{winter}	-0.015*** (0.005)	-0.001 (0.008)	-0.031*** (0.004)	0.000 (0.008)
Observations	10,968	10,961	10,966	10,358
R ²	0.923	0.913	0.954	0.978

Notes: This table shows the estimated temperature effects on output for the four agricultural sub-sectors using the baseline model specification. These estimated temperature effects can be interpreted as the percentage changes in output with a 1°C increase in temperature. Sunshine hours, rainfall, air pressure, relative humidity, and average wind speed are included as weather variables. Standard errors, shown in parentheses, are clustered within counties and within prefecture-level city-years. Units for explanatory variables: 1°C for temperature. ***p<0.01, ** p<0.05, *p<0.1

Table 5. Effects of Temperature on Agricultural Output, TFPC and Factor Inputs in Large-Livestock Regions

	Agricultural Output	TFPC	Labor	Fertilizer	Machinery	Total Planted Acres	Total Irrigated Acres
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temp ^{spring}	-0.060*** (0.008)	-0.094*** (0.012)	-0.008* (0.005)	0.003 (0.008)	0.019** (0.008)	0.035*** (0.012)	0.035*** (0.013)
Temp ^{summer}	-0.060*** (0.012)	-0.041** (0.018)	0.007 (0.006)	-0.008 (0.011)	-0.011 (0.010)	0.002 (0.006)	-0.018 (0.014)
Temp ^{spring} × “large livestock” dummy	0.026 (0.018)	0.031 (0.024)	0.016** (0.008)	0.008 (0.017)	-0.026** (0.012)	-0.036** (0.015)	-0.039* (0.020)
Temp ^{summer} × “large livestock” dummy	-0.047** (0.020)	-0.098*** (0.032)	-0.003 (0.012)	-0.008 (0.021)	0.025* (0.015)	-0.003 (0.013)	0.037 (0.026)
Temp ^{spring} effect in large livestock regions	-0.034** (0.018)	-0.063** (0.025)	0.008 (0.007)	0.011 (0.015)	-0.007 (0.011)	0.001 (0.013)	-0.004 (0.018)
Temp ^{summer} effect in large livestock regions	-0.106*** (0.019)	-0.141*** (0.031)	0.004 (0.011)	-0.017 (0.019)	0.015 (0.013)	-0.001 (0.012)	0.019 (0.025)
Observations	10,972	10,972	10,972	10,972	10,972	10,972	10,972
R ²	0.970	0.294	0.982	0.975	0.957	0.974	0.949

Notes: This table shows the effects of spring and summer temperatures on agricultural output, agricultural productivity and input use in large livestock regions. We take the natural logs for these variables, with an exception for the TFPC variable. These estimated temperature effects can be interpreted as the percentage changes in these variables with a 1°C increase in temperature. Results are obtained by constructing one new set of variables that are the interaction terms between weather variables and a “large-livestock” dummy. We then estimate equation (2) with the inclusion of the new set of the variables. All regressions include county fixed effects and region × year fixed effects, while incorporating sunshine hours, rainfall, air pressure, relative humidity, and average wind speed as additional weather variables. Standard errors, shown in parentheses, are clustered within counties and within prefecture-level city-years. Units for explanatory variables: 1°C for temperature. ***p<0.01, ** p<0.05, *p<0.1.

Table 6. Projected Impacts of Future Warming on Agricultural Output by 2050s (%)

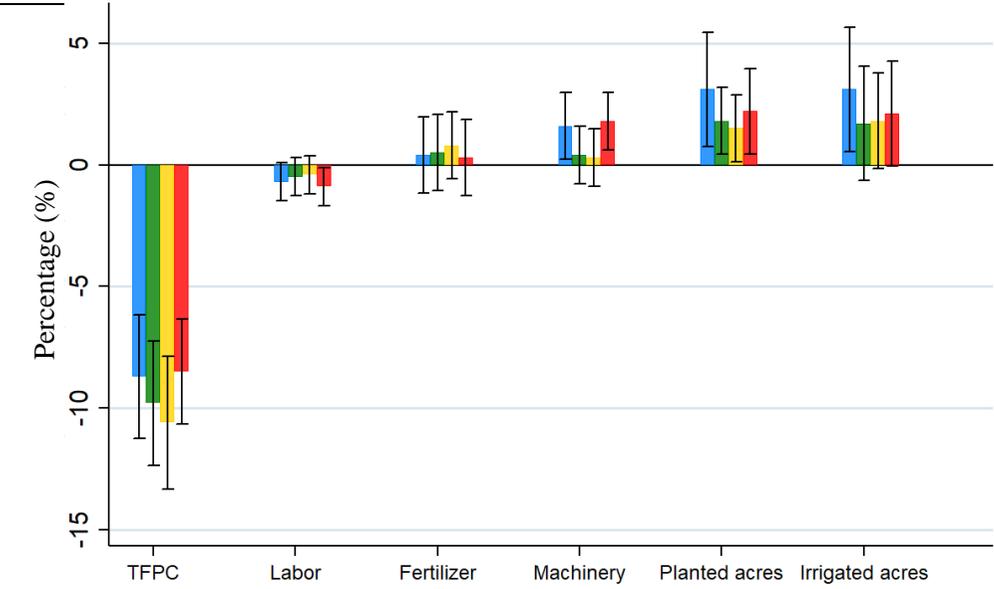
	Baseline	Scenario (1)	Scenario (2)	Scenario (3)
Warming scenarios	(1)	(2)	(3)	(4)
A2	-9.97	-10.57	-10.96	-9.33
A1B	-15.76	-16.82	-17.43	-14.92
B1	-7.12	-7.29	-7.50	-6.53

Notes: This table reports projected impacts of future warming on China's aggregate agricultural output in percentage terms under three warming scenarios (the B1, A1B and A2 scenarios) in the medium term (2050s) under the climate model UKMO-HadCM3. Column 1 reports the projections based on the coefficient estimates obtained in the baseline scenario. Columns 2-4 report the projections based on the coefficient estimates obtained in the robustness check section.

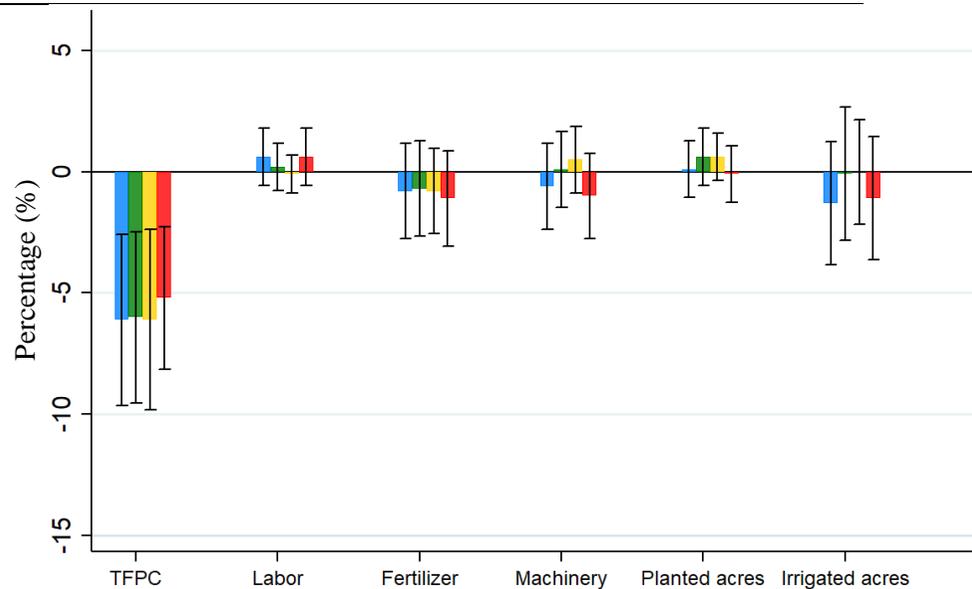
Table 7. Projected Effects of Future Warming on Agricultural Productivity and Input Use

Warming scenarios	TFPC	Labor	Fertilizer	Machinery	Total planted acres	Total irrigated acres
A2	-9.00	-0.10	2.37	0.91	4.13	2.28
A1B	-16.52	-0.11	2.71	1.60	6.51	3.64
B1	-6.87	-0.16	1.33	0.50	2.79	1.25

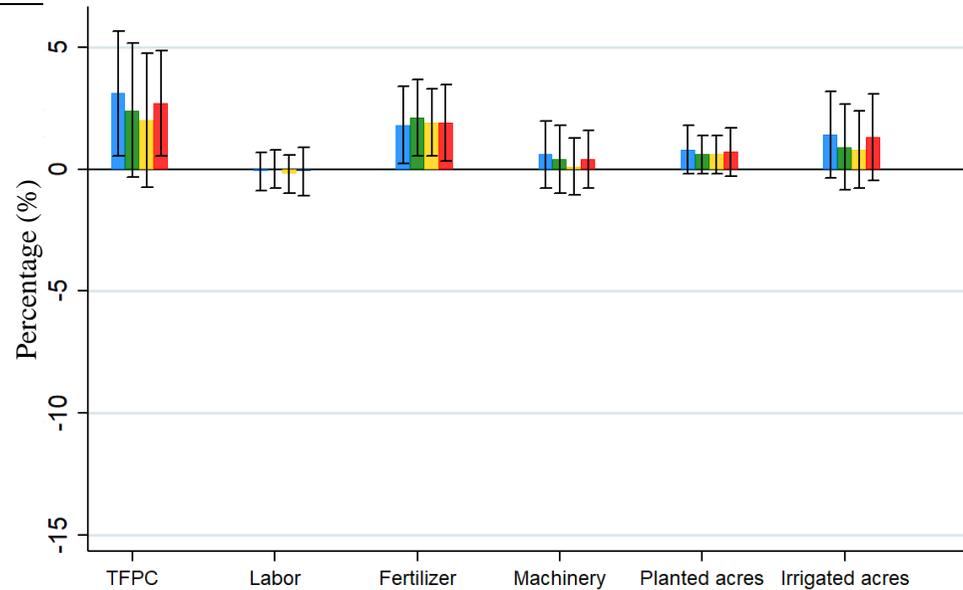
Notes: This table reports projected impacts of future warming on agricultural productivity and input use in percentage terms under three warming scenarios (the B1, A1B and A2 scenarios) in the medium term (2050s) under the climate model UKMO-HadCM3. The projected impacts are based on the coefficient estimates obtained in the baseline scenario reported in Table 2.



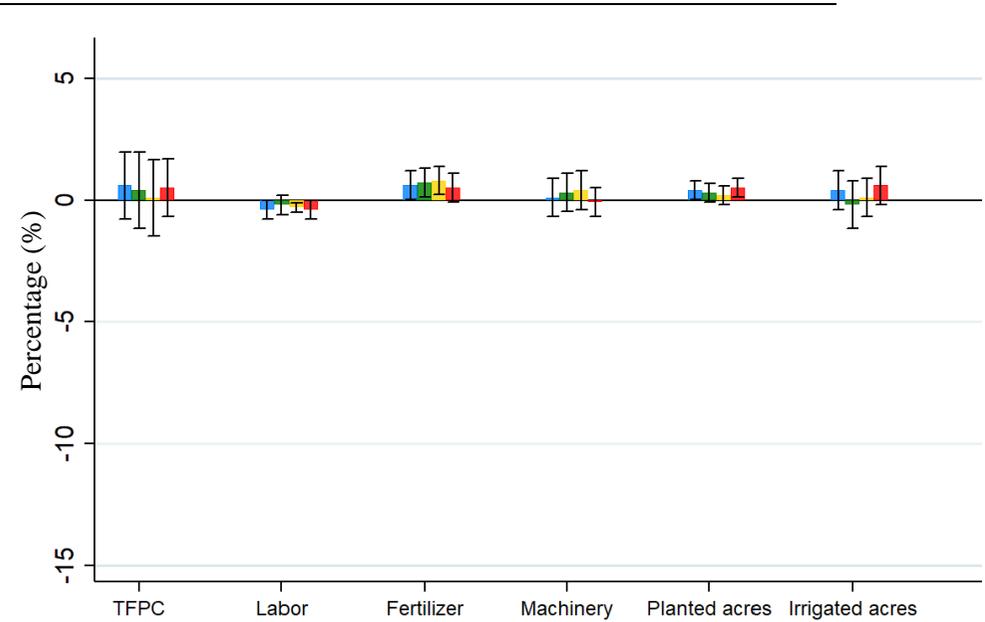
(a) Effects of higher spring temperatures



(b) Effects of higher summer temperatures



(c) Effects of higher fall temperatures



(d) Effects of higher winter temperatures



Figure 1. Temperature Effects on Agricultural Productivity and Input Use

Notes: This figure shows the contemporaneous impacts of seasonal average temperatures on TFPC and input use in percentage terms. Each cluster shows the impacts on a given variable, varied by scenario. In addition to the baseline scenario, we considered three scenarios in the sensitivity analysis. In Scenarios 1 and 2, we replace region \times year fixed effects with province \times year fixed effects and city \times year fixed effects, respectively. In Scenario 3, we remove observations if a county’s computed TFPC is either below the 2.5% level or above the 97.5% level. Bars in each cluster show point estimates of temperature variables and black lines indicate confidence bands.

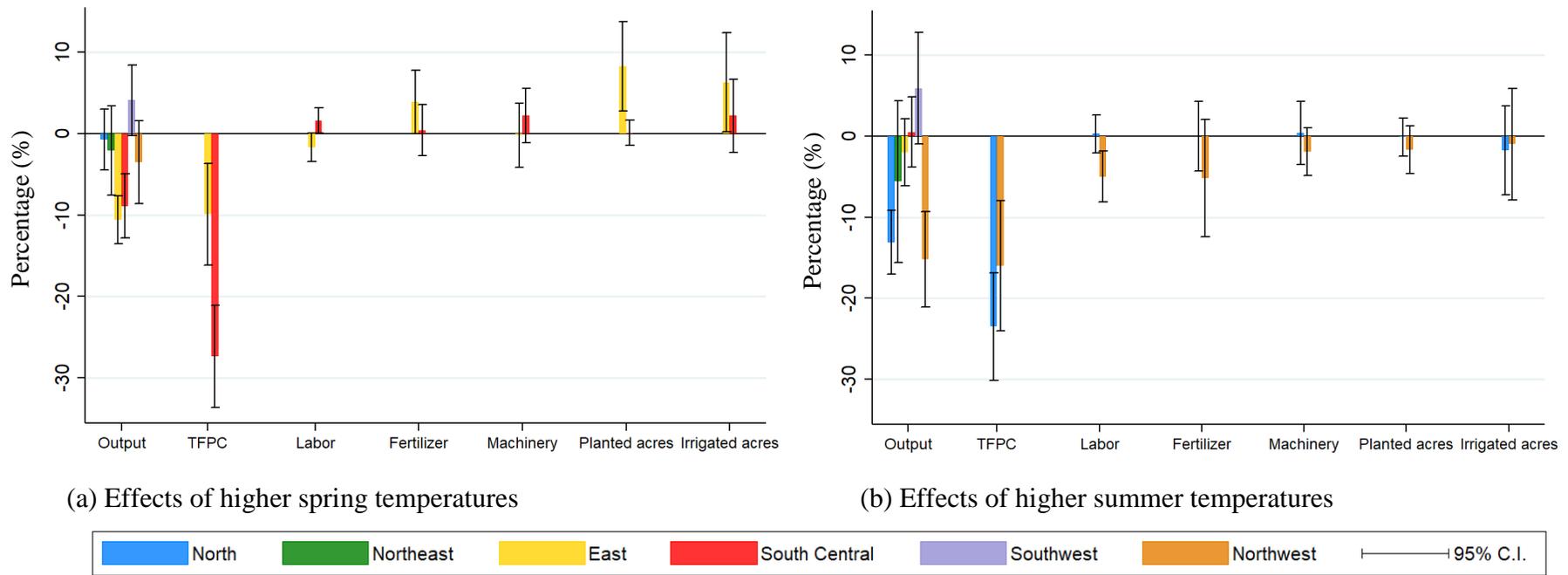


Figure 2. Heterogeneous Temperature Effects by Region

Notes: This figure shows the impacts of higher spring and summer temperatures on agricultural output, TFPC and input use in percentage terms. Each cluster shows the impacts on a given variable, varied by region. Bars in each cluster show point estimates of temperature variables and black lines indicate 95% confidence bands. For brevity, the effects of temperature on TFPC and input use are displayed only for regions whose total agricultural output is significantly affected by temperature changes.

Appendix A.

Table A1. Contemporaneous and Lagged Effects of Temperature on Agricultural Output

	(1)
Temp ^{spring}	-0.060*** (0.009)
Temp ^{summer}	-0.020** (0.012)
Temp ^{fall}	0.082*** (0.009)
Temp ^{winter}	-0.031*** (0.006)
L1: Temp ^{spring}	0.007 (0.010)
L1: Temp ^{summer}	-0.017 (0.013)
L1: Temp ^{fall}	-0.017* (0.010)
L1: Temp ^{winter}	0.016*** (0.006)
Observations	10,972
R^2	0.973

Notes: This table shows the contemporaneous and one-year lagged temperature effects on agricultural output with the baseline model specification. These estimated temperature effects can be interpreted as the percentage changes in output with a 1°C increase in temperature. Sunshine hours, rainfall, air pressure, relative humidity, and average wind speed are included as additional weather variables. Standard errors, shown in parentheses, are clustered within counties and within prefecture-level city-years. Units for explanatory variables: 1°C for temperature. ***p<0.01, ** p<0.05, *p<0.1

Definitions of Chinese Regions:

China is grouped into six traditional regions:

1. North: Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia;
2. Northeast: Liaoning, Jilin, and Heilongjiang;
3. East: Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong;
4. South Central: Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan;
5. Southwest: Chongqing, Sichuan, Guizhou, Yunnan, and Tibet;
6. Northwest: Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.