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Capacity to Adapt to Temperature Effects on Crop Yields: Evidence from Rice Production in Japan

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Abstract

The main purpose of our paper is to explore mechanisms of farmer's adaptation to climate change. Specifically, we assess the farmer's adaptation capacity to extremely low and high temperatures by quantifying the effect of farmer's age and experience on the temperature-yield relationship. We estimate their effects by conducting the panel (short-run adjustment) and long-differences (long-run adaptation) analyses following Burke and Emerick (2016) with the municipality-level rice yield data in Japan from 1993 to 2018. We find that both age and experience of extreme temperatures are significant factors that strengthen the farmer's adaptation capacity to climate. Age is more likely to help farmers adjust to annual weather fluctuations than to assist long-term adaptation to climate, whilst the past experience of extreme temperatures rather encourages farmers to adapt to the climate in the long run.

Keywords: Adaptation capacity, Age, Rice, Climate change, Crops yields, Temperature
JEL classification: Q10, Q51, Q54

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l. Introduction

Global warming is a serious future risk to our society and the extreme heat is likely to decrease crop yields (e.g., Schlenker and Roberts 2009; Burke and Emerick 2016; Chen et al. 2016; Kawasaki and Uchida 2016; Aragón et al. 2021). Diminution in productivity is anticipated to cause a decline in crop production which directly affects the future food supply. To be food secure, it is essential to understand how farmers respond to climate change. For instance, if farmers switch from growing a less heat-tolerant crop to a more warmth-resistant one under warming, the economic loss associated with temperature rise would reduce. Nevertheless, if farmers take no action against the increasing heat, the overall damage could be excessively enormous. An efficient policy design requires a superior comprehension of how quickly the producers adopt significant measures against environmental change.

When it comes to the evaluation of climate change effects associated with adaptation on crops, the biophysical models are often used in the early work (e.g., Ford and Thorne 1967; Acock and Allen 1985; Adams et al. 1990). However, experimental results of these models may not fit in real-world settings since they do not straight rely on observational data. Empirical economic studies frequently apply the Ricardian approach (e.g., Mendelsohn et al. 1994; Schlenker et al. 2005, 2006) and the panel analysis (e.g., Deschênes and Greenstone 2007, 2012; Schlenker and Roberts 2009; Agostino and Schlenker 2016) to implement corresponding evaluations. Nonetheless, the omitted variable bias concern in the cross-sectional design has been pointed out. Hence, panel analysis becomes preferable since the time-invariant variables (soil quality, etc.), which have often been criticized for correlating with temperature, are absorbed by fixed effects. Despite that, year-to-year variation of the longitudinal data only allows us to explore the short-term weather impact on crops. From the policy perspective, it is important to perceive the responsiveness of crops to warming in both the short and long run (the long-term analysis is expected to capture the farmer's adaptation behaviors to local climate). Recently, an alternative path, the long differences approach, that addresses the omitted variable bias disquiet in the cross-sectional regression is introduced (Burke and Emerick, 2016).

While a broad set of adaptation technologies such as the adoption of new crop varieties and adjustment of cropping season have been available to farmers, whether and how to adapt depends also on farmers. Many studies find that the farmer's adaptation capacity is determined by his/her characteristics such as age and experience (e.g., Barnes 2019; Niles et al. 2015; Shang et al. 2021), but we do not know how these characteristics play a catalytic role in mitigating the negative temperature effects on crop production by enhancing the farmer's adaptation capacity. Especially aging of the farming population arises in Japan as well as in the US and Europe. Therefore, it is important to understand how aging is likely to affect the impact of temperature to consider the future adaptation capability.

The purpose of our paper is to assess whether farmer's age and experience mitigate the negative effect of extreme temperatures on crop yields. Elderly farmers are more likely to have a lack of ability to new technology adoption (Shang et al. 2021) and/or less incentive for its adoption due to the close retirement (Barnes 2019), hence their crop production is more susceptible to extreme temperatures in the short run. On the other hand, learning from past experience in climate-related extreme events tends to alter farmer's perception of climate change (Niles et al. 2015) and thereby urge the farmer's adaptation behavior in the long run. Our study is the first to quantify how and to what extent farmer's age and experience influence the adaptation capacity to negative temperature effects on crop yields in both the short- and long-term.

We demonstrate this by using Japanese paddy rice production as a case study. Japan is famous for aging society, and it is also true for the agricultural population. Aging of the agricultural population poses a threat to the stability of food security (Jöhr 2012; Poungchompu et al. 2012)[1]. By using the municipality-level data on rice production in 1993 to 2018, we utilize the unique incidence of the "Rice Riots of 1993" when the abnormally cold summer hit and farmers particularly in northern Japan experienced historic damage on their rice production[2]. We estimate the effects of farmer's age and experience of this extreme temperature event on the temperature-yield relationship by conducting both the panel (short-run adjustment) and long-differences (long-run adaptation) analyses following Burke and Emerick (2016).

The main findings of this study are as follows: (1) Farmer's age appears to have diminishing marginal benefits to the temperature-yield relationship and age of 55-61 years old are the most resilient to extreme temperatures; (2) Farmer's age seems to play a more important role in improving farmer capacity to adjust to annual weather fluctuations than to assist long-term adaptation to climate; (3) The experience of an extreme temperature event encourages farmers to cope effectively with negative climate effects; and (4) As a result, the negative effects of extreme cold and hot temperatures

[1] According to the Agricultural Censuses, the share of core persons mainly engaged in farming aged 65 and over increased from 20% in 1985 to more than 60% in 2015, see Agriculture and Forestry Census (https://www.maff.go.jp/j/tokei/census/afc/about/setumei.html) for more information.

[2] Rice crops situation index (normally around 100) fell to 40-60 in northern Japan, which was not experienced over the last 50 years.

decline in the long run, suggesting farmer's adaptation to the local climate.

The remainder of this paper is organized as follows. Section ll describes the background of Japanese rice production and aging population, and the methodology used in previous literature. Section lll discusses the empirical methodology and data. Section IV represents estimation results. Section V concludes.

ll. Background and Previous Studies

A. Background

Rice is a staple crop in Asian countries including Japan[3], which plays a major role in preserving the food supply and farmer income. In addition, rice is extremely vulnerable to temperature. For instance, cold damage has been a serious problem in northern Japan (relatively cold temperature area). The most well-known incident is the "Rice Riots of 1993", which was when Japan suffered from the shortage of rice due to the abnormally cold summer in the year 1993, the scarcity situation was much more severe in northern Japan. The crop situation index (CSI) of rice dropped to 74[4], a level that has not been seen in recent years. Previous agronomic studies devote adequate effort to understanding how cold damage affects rice growth (Taniguchi 1979; Satake 1980), additionally, create the early-warning system to reduce the loss of rice on account of the cold temperatures (Kanda 2007). The Japanese government has also been dedicated to developing and cultivating the cold-tolerant breed of rice to protect rice against the colds.

Moreover, not only colds but also heat affects the rice growth, the hot temperature mostly brings economic damage to rice in southern Japan (relatively hot temperature area). The tendency of high temperature during the rice-growing season is remarkable from the 2000s in Japan, which leads to the occurrence of white immature grains. Morita (2008) finds that the threshold of daily mean temperature in the 20 days after the rice heading date which causes the increase in the occurrence of the white immature grains, is approximately 26 to 27 degrees Celsius. Furthermore, high temperature is likely to decrease the rice quality (Kawatsu et al. 2007; Okada et al. 2011; Kawasaki and Uchida 2016) and production except for northern Japan (Yokozawa et al. 2009). Over recent years, the Japanese government has started innovating and planting the heat-tolerant variety of

[3] Rice accounts for 19.2% of agricultural output in Japan in 2018. See MAFF Statistics Agricultural Income Produced (https://www.maff.go.jp/j/tokei/kouhyou/nougyou_sansyutu/) for more detailed information.

[4] See report from Suitō no Sakugara ni Kansuru Iinkai (https://www.maff.go.jp/j/study/suito_sakugara/) for more detailed information.

rice. According to the special report by IPCC in 2018, global warming tends to increase the surface temperature by 1.5°C between 2030 and 2052 if it continues to expand at the current speed[5]. To achieve an efficient policy design to stave off the farmer income loss under climate change, being knowledgeably aware of the responsiveness of rice to temperature rise and how quickly agents react to the changing climate is of considerable importance.

The aging farming population is threatening food security by diminishing farmer adaptation capacity to extreme temperatures. According to the Census of Agriculture and Forestry by MAFF in 2015, the average age of core persons mainly engaged in farming has reached 67 years old, up 7.2 years from the last decade. The outflow of young people from rural areas to urban areas is accelerating the aging of rural areas (Kato 2003). Many studies find that the farmer's adaptation capacity is determined by his/her characteristics such as age and experience (e.g., Barnes 2019; Niles et al. 2015; Shang et al. 2021), but how these characteristics play a key role in alleviating the negative temperature effects on crop yields by strengthening the farmer's adaptation magnitude remains unclear. Elderly farmers tend to be deficient in the capability to new technology adoption (Shang et al. 2021) and/or reduced motivation for its adoption owing to the near retirement age (Barnes 2019), resulting in a larger sensitivity of crop production to extreme temperatures in the short run. On the other hand, learning from earlier experience in climate-related extreme events is likely to improve farmer's awareness of climate change (Niles et al. 2015) and by that means to prompt the farmer's adjustment practices in the long run. Comprehending age and experience effects on the temperature-yield relationship can give us useful policy insights to avoid the further loss of crop yields under the aging farm community.

Figure 1 presents the change in temperature over the study period 1993-2018. We denote the difference in average daily mean temperature during the growing season between 1993-1997 and 2014-2018 periods. The temperature has increased in almost every city over the 26 years (an average 0.8-0.9℃ increase and a maximum 1.5-1.6℃ increment). Figure 2 and Figure 3 indicate the difference between the average rice yields in each city and the average in Japan. In the 1993-1997 period, rice productivity in northern Japan is smaller than the average productivity in the whole of Japan. Nonetheless, in the later period (2014-2018), rice yields in the northern part of Japan gradually exceed the average in Japan while in southern Japan, yields turn out to be under the national average. We reveal that the rice sector in Japan has experienced a trifling yields growth along with the increase in temperature during the period 1993-2018 (see Figure A1 in

[5] See Special Report: Global Warming of 1.5 ºC (IPCC, 2018) for detailed information.

Appendix), note that there is a plumb line in the year 1993, which could be largely attributed to the stern cold damage.

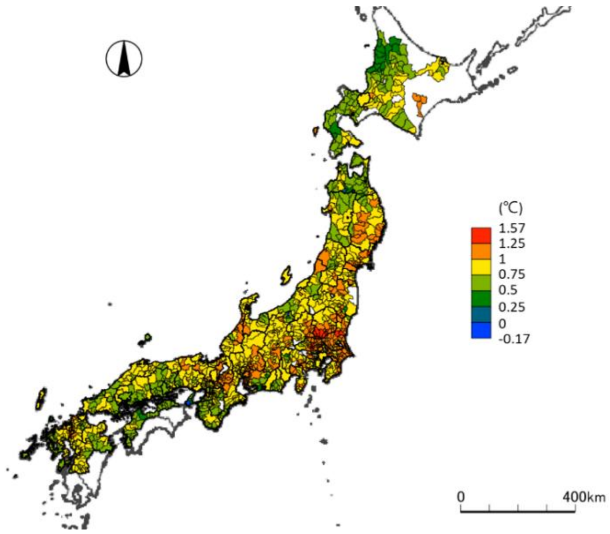

Figure 1. Change in Temperature (°C) Over the Period 1993-2018

Notes: Temperature is measured over the rice-growing season in Japan (Apr. to Oct.) in each study city Information is not provided for white-colored cities, which are not targeted in our study because of no rice production or double cropping. See Figure 4 for more detailed information.

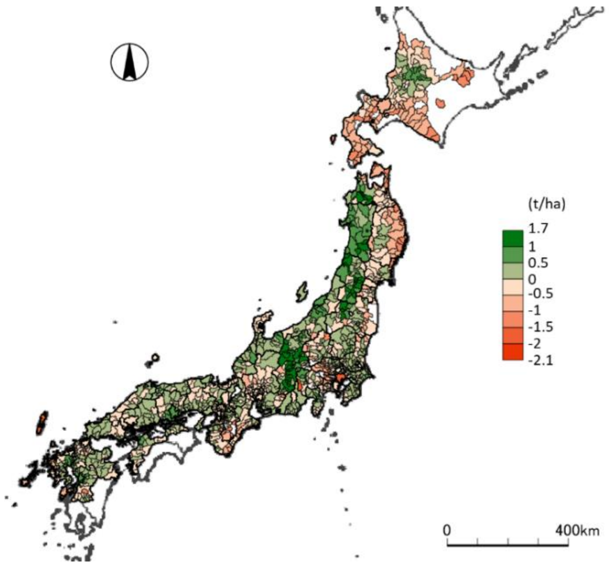

Figure 2. Difference between Rice Yields (t/ha) in Each Study City and Whole Japan Over the Period 1993-1997

Notes: Information is not provided for white-colored cities. See Figure 4 for more detailed information.

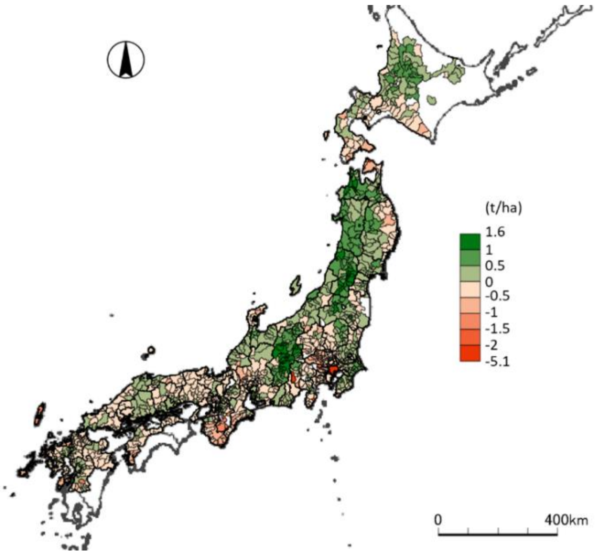

Figure 3. Difference between Rice Yields (t/ha) in Each Study City and Whole Japan Over the Period 2014-2018

Notes: Information is not provided for white-colored cities. See Figure 4 for more detailed information.

B. Previous Studies

When assessing the impact of climate change and adaptation in the agricultural sector, biophysical models are often used in early work (Moe 1977; Acock and Allen 1985; Allen et al. 1987; Idso et al. 1988; Adams et al. 1990). The main advantage of applying this approach is that we can directly realize the impact of specific climate conditions and farmers' adaptation on our interest output considering that we design the scenarios, for instance, the concentration of carbon dioxide and the ideal growing period according to our curiosity and needs. Despite that, since the experiments mostly are not based on historical data, the results may not fit in the reality. From the economic perspective, the Ricardian approach is widely used in previous studies (Mendelsohn et al. 1994; Eid et al. 2007; Seo and Mendelsohn 2008; Chatzopoulos and Lippert 2015; Ortiz-Bobea 2019) to explore the long-term climate impact on economic output (farmland value, etc.). The major advantage of using the Ricardian model is that the point estimates account for the full range of farmers' adaptation. The problem is we are not likely to define the impact of specific adaptation on our interest outcome. The other concern of this approach which has generally been criticized is the omitted variable bias owing to the correlation between unobservable time-invariant factors (soil quality, etc.) and temperature variables. Consequently, the panel approach is more favored in recent years to avoid analogous estimation bias by operating fixed effects (Deschênes and Greenstone 2007, 2012;

Schlenker and Roberts 2009; Agostino and Schlenker 2016; Cui and Xie 2021; Miller et al. 2021). Nevertheless, as panel analysis uses year-to-year variation in the regression model, it only allows us to capture the short-term weather impact on agricultural output and fails to control the farmers' adaptations in the long run, From the policy perspective, both short-and long-term economic impacts are of substantial influence.

To capture the long-term climate change impact and address the omitted variable bias, an alternative approach, the long differences approach, is introduced (Burke and Emerick, 2016). The main concept of the long differences approach is that in the regression, we take the first difference between two periods (each period is calculated by the multi-year average), the time-invariant variables are, therefore, dropped. Hence, we can evaluate the long-term climate impact avoiding the omitted variable bias concern. In this study, we apply both panel analysis and long differences approaches to denote the short-term and long-term responsiveness of rice yield to temperature in Japan, respectively. Note that following Burke and Emerick (2016) we assume the parameter of independent variables in the long differences approach are the same as those specified in the panel analysis. Additionally, the parameters in the long-term analysis are anticipated to make the response function flatter in the existence of farmer's adaptation.

lll. Methodology and Data

A. Methodology

In this study, we aim to evaluate the effects of farmer's age and experience on both the short- and long-term sensitivity of rice yields to temperature. We apply the panel approach which captures the weather shock impact by using the year-to-year variation for the short-term analysis. The main limitation of this approach is that we are not able to capture farmer's adaptation behaviors in the long run. The Ricardian approach is broadly used to explore the long-term temperature impact reflecting the full range of adaptation practices, but the omitted variable bias due to the correlation between the unobservable time-invariant factor (such as climate) and temperature variables has been pointed out. Thus, to address this drawback, Burke and Emerick (2016) propose the long differences approach, to inspect the temperature effects in the long run. Following their work, we examine the long-term responsiveness of rice yields to temperature in Japan. Note that as is in Burke and Emerick (2016), we assume the parameter of independent variables in the long differences approach are the same as those specified in the panel analysis.

1. Panel Approach— Short-Term Impact

Our baseline panel specification is given by:

$$(1)\ \ln(\mathrm{Y}_{it}) = \alpha_0 + \beta_1^{short}\mathrm{GDD}_{\leq T_{it}} + \beta_2^{short}\left(\mathrm{GDD}_{\leq T_{it}} \times \mathrm{Adapt}_{it}\right) + \beta_3^{short}\mathrm{GDD}_{>T_{it}} +$$

$$\beta_4^{short}\left(\mathrm{GDD}_{>T_{it}} \times \mathrm{Adapt}_{it}\right) + \mathbf{Z}_{it}\gamma + \mathrm{C}_i + \lambda_{pt} + \varepsilon_{it},$$

where Y_{it} is the rice yield in the city *i* in year *t*, $\mathrm{GDD}_{\leq T_{it}}$ measures the sum of heat that crops receive between the lower bound temperature threshold and upper bound temperature threshold (T) over the growing season, we set the upper bound threshold as 0°C following Burke and Emerick (2016), $\mathrm{GDD}_{>\mathrm{T}_{it}}$ similarly measures the cumulative heat above T over the growing season[6], Adapt_{it} represents farmer's age, experience, and farm productivity to measure the adaptation capability, a vector $\mathbf{Z}_{it}$ includes the average daily precipitation and global solar radiation over the growing season and their quadratic terms, and farmer's characteristic variables. Due to the availability of the data, we use the general farmer information of the number of farm households per total cultivated land area, single and square terms of farmer average age, percentage of full-time farm household[7], and percentage of the business farm household[8]. We use rice farmer information of rice transplanters per rice planted area and rice planted land area per rice farm household, C_i is the city fixed effect, λ_{pt} is the prefecture by year fixed effect, and ε_{it} indicates the error term.

2. Long Differences Approach— Long-Term Impact

Our baseline long differences estimation is as shown below:

$$(2)\ \Delta\ln(\mathrm{Y}_i) = \beta_1^{long}\Delta\mathrm{GDD}_{\leq T_i} + \beta_2^{long}\Delta\left(\mathrm{GDD}_{\leq T_i} \times \mathrm{Adapt}_i\right) + \beta_3^{long}\Delta\mathrm{GDD}_{>T_i} +$$

$$\beta_4^{long}\Delta\left(\mathrm{GDD}_{>T_i} \times \mathrm{Adapt}_i\right) + \Delta\mathbf{Z}_i\theta + \tau_p + \Delta\varepsilon_i,$$

[6] For example, if T = 19 and a set of daily temperatures is -1, 15, 18, 21 and 24, $\mathrm{GDD}_{\leq T_{it}}$ is equal to 0, 15, 18, 19 and 19, and $\mathrm{GDD}_{>T_{it}}$ is equal to 0, 0, 0, 2 and 5.

[7] Number of general full-time farm households/ Total number of general farm households

[8] Number of general business farm households/ Total number of general farm households

where ΔY_i is the first difference in rice yield in the city i between a and b periods, variables of a and b periods are calculated by using the multi-year average respectively, for example, taking the 10-year average. Thus, period a represents the 10-year average over 1993-2002 and period b indicates the 10-year average over 2009-2018. $\Delta \mathrm{GDD}_{\leq T_i}$ and $\Delta \mathrm{GDD}_{>T_i}$ give the change in average degree days below and above the threshold between two periods, respectively. $\Delta\left(\mathrm{GDD}_{\leq T_i} \times \mathrm{Adapt}_i\right)$ and $\Delta\left(\mathrm{GDD}_{>T_i} \times \mathrm{Adapt}_i\right)$ show the change in degree days below and above the threshold multiply by farmer's age, experience, and farm productivity between two periods, respectively. $\Delta \mathbf{Z}_i$ presents the difference in average daily precipitation and global solar radiation between two periods and the difference in their quadratic terms. Additionally, we control the unobservable variable that does not vary over time within each prefecture (τ_p) in the regression.

B. Data

1. Agriculture Data

The agriculture data used in this paper is obtained from Ministry of Agriculture, Forestry and Fisheries (MAFF)[9]. We have the annual data of rice planted area and rice production from 1993 to 2018 (26 years) at the city level [10,11]. Based on the rice planted area and rice production data, we calculate the rice yield in each year for each city. Farmer characteristic data (farmer age, etc.) is attained from quinquennial agricultural censuses[12]. Due to the limitation of electronic data, we employ the year 2000, 2005, 2010, and 2015 census information at the city level.

2. Weather Data

The weather data applied in this paper is acquired from Agro-Meteorological Grid Square

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[9] See Ministry of Agriculture, Forestry and Fisheries (https://www.maff.go.jp/) for more detailed information.
[10] See MAFF Statistics Sakumotu Tokei Sakkyou Kome (https://www.maff.go.jp/j/tokei/kouhyou/sakumotu/sakkyou_kome/index.html) for more detailed information of data.
[11] Municipal mergers were carried out nationwide in the mid-2000s, and the number of cities has decreased about half. We merge the data to the city which existed in 2018. The information on municipal mergers is from MAFF Statistics Sakumotu Tokei Sakkyou Kome.
[12] See Agriculture and Forestry Census (https://www.maff.go.jp/j/tokei/census/afc/about/setumei.html) for more detailed information.

Data, NARO[13]. They provide 14 types of daily meteorological weather data by 1km square (third-order grid unit) for the whole of Japan. Three weather variables are used in this study: daily mean temperature, daily precipitation, and daily global solar radiation, which are the key factors that affect the growth of rice. The periods of the weather data are from 1993 to 2018. In addition, we merged the grid-level data to city-level data according to the list of mesh codes by city provided by the Statistics Bureau of Japan.

We focus on the single cropping cities in Japan which continuously produce rice[14]. Figure 4 presents the rice-growing status of each city in Japan, single cropping cities account for 90.2% of cities in Japan (9.8% belong to double cropping). Additionally, among single cropping cities, 92% of them continuously grow rice (5.4% of cities never produce rice, 1.4%/0.2% originally produced/did not produce but eventually quit/start growing rice, 1% others). As a result, selection bias is not likely to happen in our case. We concentrate on the weather data during the rice-growing season (April to October) which affects rice production.

Table 1 presents the characteristic of the main variables in our study. The average rice yield among study cities is 5 tons per hectare and it varies across the cities. Average daily mean temperature, average daily precipitation, and average daily global solar radiation during the growing season, 1993-2018 are 18.5°C, 5.7 mm, and 15.2 MJ/m2, respectively. The average farmer age in Japan during the 1993-2018 period is 57 years old. The variations of these variables are quite large.

Table 1–Summary statistics

	Obs.	Mean	SD	Min	Max
Rice Yield (t/ha)	36,713	4.98	0.68	0.002	9.00
Mean Temperature (°C)	36,713	18.49	2.85	7.87	23.75
Precipitation (mm/day)	36,713	5.65	1.96	1.47	22.16
Global Solar Radiation (MJ/m2/day)	36,713	15.19	1.26	10.98	22.36
Age (years old)	36,713	57.27	3.17	48.10	71.60

Notes: The values are yearly average at the city level. Only Apr. to Oct. data is used for weather variables.

[13] See Agro-Meteorological Grid Square Data, NARO (https://amu.rd.naro.go.jp/wiki_open/doku.php?id=start) for more detailed information.

[14] In Japan, there are 47 prefectures in total, 42 prefectures conduct single cropping and 5 prefectures (Tokushima, Kochi, Miyazaki, Kagoshima, and Okinawa) perform double cropping for paddy rice. Those 5 prefectures are excluded in this research.

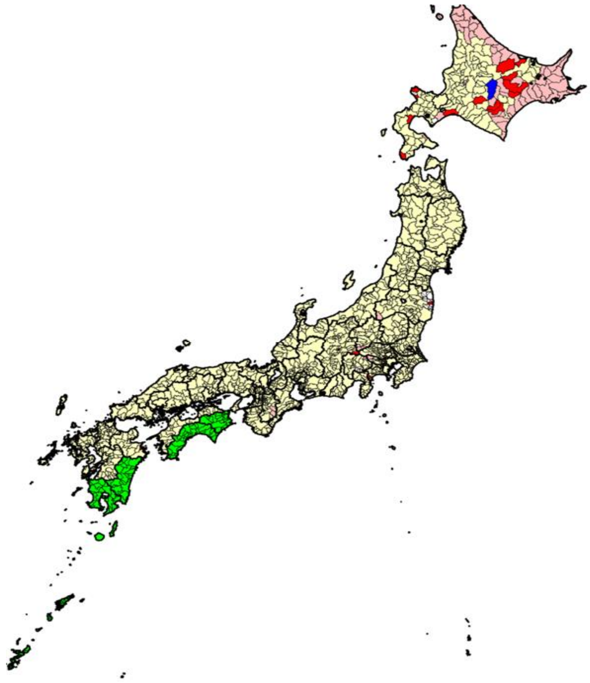

Figure 4. Rice Growing Status of Each City in Japan Over the Period 1993-2018

Notes: The pink color indicates the cities which never produce rice. Yellow presents the cities which continuously grow rice. Red (or Blue) color shows the cities which originally produced (or did not produce) rice but eventually quit (or start) growing rice. Green gives the double-cropping area, which is excluded in our study.

IV. Empirical Results

A. Baseline estimations

The base estimation results of yields are presented in Table 2. Columns 1 and 3 are our benchmark models for panel and long differences, respectively. In Columns 2 and 4 we add the other control variables. Threshold temperatures are found to be 19℃ and 16℃ in the panel and long differences, respectively based on model fitness. Appendix Table A1 and A2 give the model fits under different temperature thresholds for both the panel and long differences. Our work focuses on the whole period of the rice-growing season, which leads to a smaller threshold temperature relative to agronomics, in Appendix B we show that our results remain comparable with agronomics when we apply a similar study period as agronomists[15]. In the long differences approach, Columns 3-4, we use the

[15] Morita (2005) finds that the rate of occurrence of white immature grains begins to rise when the average daily mean temperature for 20 days after heading exceeds 23 to 24℃. The maximum grain

differences between the 1993-2002 and 2009-2018 periods (10-year average). We obtain similar estimation results when we change the number of years (5-9 years) for each period to calculate the yearly average. The model fits under different multi-year averages are revealed in Appendix Table A3.

Both the panel and long differences models deliver consistent temperature results for estimations with and without the inclusion of the other control variables. Compare with our threshold temperatures, we find the negative responsiveness of rice yields to the temperature below and above the threshold. In our base panel specification, exposure to each additional degree-day of temperature below and above the threshold reduces rice yields by 0.08 percent by 0.04 percent respectively. On the other hand, in the long differences model, they reduce yields by 0.06 percent and 0.03 percent respectively. From these results, we notice that rice productivity in Japan is more vulnerable to cold temperatures, which corresponds to Kawasaki and Uchida (2016). Cold damage has been a serious problem rather than hot damage especially in the northern part of Japan, which causes the inhibition of pollen formation and sterility (fertilization disorder) of rice. We interpret that the parameters of temperature below the threshold capture such cold damage. By comparing the panel and the long differences results, we indicate that the negative sensitivity of rice yields to the temperature below and above the threshold was reduced by 20 percent and 29 percent respectively in the long run because of long-term adaptations. However, it should be noted that the differences in parameters between the panel approach and the long differences approach are not significant (see Appendix Table-A4)[16]. The graphical results of the panel and long differences are given in Figure 5 (we take Columns 1 and 3 in Table 2 for comparison).

To test the robustness of our results in Table 2, in Appendix Figure A4, we indicate that our results are consistent when we change the clustering level and in Appendix Figure A5, we provide further evidence that our current frameworks are insensitive to the model selections by conducting bin (1-degree Celsius interval), step (3-degree Celsius interval), and simple polynomial (2nd and 5th orders) functions following previous literature (e.g., Schlenker and Roberts 2009; Burke and Emerick 2016; Kawasaki and Uchida 2016; Cui et al. 2021).

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weight was observed at 24°C in Wakamatsu et al. (2007) and 19 to 25°C in Yoshida and Hara (1977). In Appendix B, we use the three weeks weather data after the average heading date, 1993-2018, to evaluate the temperature effects on rice yields and how farmer's age and their past extreme event experience affect temperature-yield relationship. We find that: (1) Two-threshold case has better model performance than only consider one and (2) The optimal temperature is found to be 24°C and middle threshold is found to be 18°C, which are consistent with previous literature.

[16] Following Burke and Emerick (2016), we bootstrap our data 1,000 times and recalculate the ratio of extreme colds and heat coefficients between the panel and long differences models.

Table 2—Panel and long differences estimates
of the impacts of temperature on rice yields

	Panel	Panel	LD	LD
	(1)	(2)	(3)	(4)
GDD below	0.0008***	0.0008***	0.0006***	0.0006***
threshold	(0.0001)	(0.0001)	(0.0002)	(0.0001)
GDD above	-0.0004***	-0.0004***	-0.0003***	-0.0002***
threshold	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Precip	-0.0046	-0.0041	-0.0156	0.00003
	(0.0032)	(0.0031)	(0.0121)	(0.0118)
Precip^2	0.0002	0.0002	0.0011	0.0002
	(0.0002)	(0.0002)	(0.0009)	(0.0008)
Radiation	0.1612***	0.1467***	0.0024	-0.0219
	(0.0475)	(0.0464)	(0.0210)	(0.0213)
Radiation^2	-0.0049***	-0.0044***	-0.0001	0.0007
	(0.0015)	(0.0014)	(0.0006)	(0.0006)
Obs.	36,713	36,713	1,384	1,384
FE	City, Pref-Year	City, Pref-Year	Prefecture	Prefecture
Control var.	No	Yes	No	Yes
Adj. R^2	0.6824	0.6838	0.5875	0.6279
F statistic	11.72	6.62	5.25	4.73
T threshold	19°C	19°C	16°C	16°C

Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. Columns 1-2 are estimated with an annual panel and use piecewise linear thresholds as selected by the panel model, and 3-4 with long differences and use thresholds as selected by the long differences model. Columns 1 and 3 are our baseline models for panel and long differences, respectively. Columns 2 and 4 are estimated with additional control variables shown at the bottom; see main text for details. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

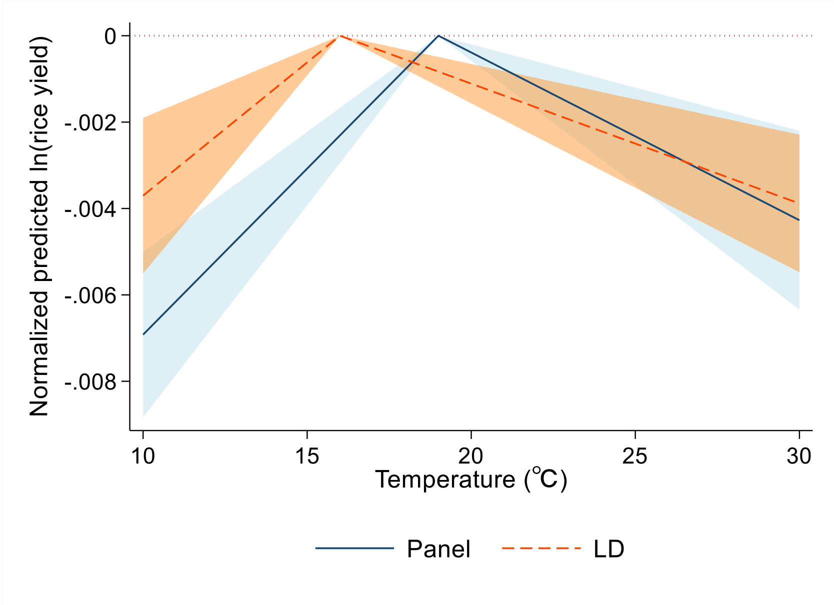

Figure 5. Relationship Between Temperature and Rice Yields

Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at threshold temperature, as evaluated by the panel (solid) and long differences models (dash). The shaded areas are 95 percent confidence intervals.

B. *Farmer Capacity to Adapt to Temperature Effects*

To reduce the negative temperature effects on rice yields, farmer's adaptation capacity is of considerable importance. For instance, farmer's experience may help to decrease the yields loss due to the extreme temperature events. On the other hand, aging farmers may have less potential to cope with abnormal temperature events because of health conditions or reduced cognitive capability. To measure such adaptation capacity of the farmers, we use the data of the average farmer's age and rice crops situation index in the year 1993 (Rice Riots of 1993) to capture farmer's experience of extreme temperature experience. We assume that elder farmers tend to alleviate the negative temperature impacts on yields because of more experience and elder farmers beyond some threshold age mitigate the yields loss less[17]. To capture the inverted U-shaped link between farmer age and the impact of temperature on rice yields, we add the cross-terms of GDD variables with single and square terms of farmer's age. To capture the impact of the experience of extreme temperature events, we add the cross-terms of GDD variables with the rice crops situation index.

Results of the panel and long differences are shown in Table 3 and display that farmer

[17] Tauer (2017) finds that farmer productivity has a concave relationship with farmer age.

age has an inverted U-shaped relationship and the threshold age that minimizes the negative impact of the temperature is found to be 61 years old in the panel approach and 55 years old in long differences. Once the farmer's age exceeds the threshold age, farmer adaptation capability is decreased. Note that the threshold age is 6 years younger in the long run, implying that farmers need to be younger to adapt to the temperature change in the long run because they need more cognitive skills to adapt in the long run, for example, to understand new technology and new characteristics of new rice brand[18]. We present the

Table 3–Effect of adaptation capacity of farmer's age

	Panel	LD
	(1)	(2)
GDD below	0.0140**	0.0095**
threshold	(0.0056)	(0.0043)
GDD below	-0.00044**	-0.00032**
threshold × age	(0.00019)	(0.00015)
GDD below	0.0000036**	0.0000029**
threshold × age^2	(0.0000016)	(0.0000013)
GDD above	-0.0101*	-0.0046*
threshold	(0.0059)	(0.0028)
GDD above	0.00032	0.00015
threshold × age	(0.00020)	(0.00010)
GDD above	-0.0000025	-0.0000013
threshold × age^2	(0.0000017)	(0.0000008)
Obs.	36,713	1,384
FE	City, Prefecture-Year	Prefecture
Adj. R^2	0.6839	0.5987
F statistic	7.66	4.22

Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. Both estimations include single and square terms of precipitation, global solar radiation, and age. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

[18] Age is found to be a barrier to new technology adoption possibly because new technologies are too complex (Shang et al. 2021) or closer retirement makes the investment decision of older farmers myopic (Barnes 2019).

graphical results of both short- and long-term temperature effects on yields under three age scenarios in Figure 6, and our main findings are twofold: (1) Farmer's age seems to affect the adaptation capability because of their experience, cognitive skills, etc. (2) The threshold of age to minimize the negative temperature effect on the yield is younger in the long run because higher cognitive skill is required for long-run adaptation.

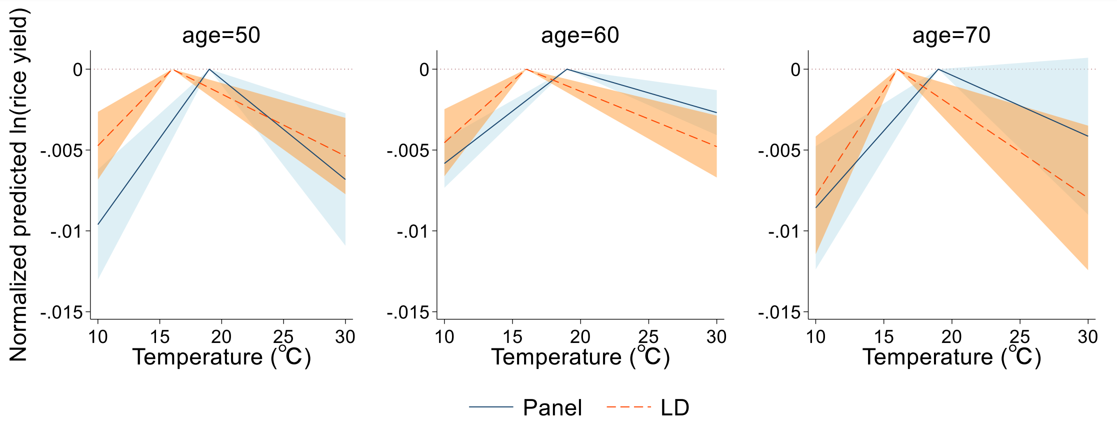

Figure 6. Relationship Between Age-Temperature and Rice Yields

Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at threshold temperature, as evaluated by the panel (solid) and long differences models (dash) considering several age scenarios. The shaded areas are 95 percent confidence intervals.

To further explore whether extreme event experience affects the farmer's capacity to adapt to severe temperatures, we add the interaction term of GDD variables and the dummy variable of experience of the extreme cold temperature event, which equals 1 if farmers suffered from the cold damage in the year 1993[19] to equation (1) and (2). The graphical results of both estimations are presented in Figure 7. We find that farmers that experienced the cold damage in the year 1993 tend to reduce the negative cold temperature effects in the long run while we do not observe the same effect.

[19] Farmers with cold damage experience are defined as the crop situation index (CSI) in 1993 smaller than 2 standard deviations of average CSI during 1979-1992. Note that only prefecture-level CSI data from the year 1979 is available on the MAFF website. See report from Suitō no Sakugara ni Kansuru Iinkai (https://www.maff.go.jp/j/study/suito_sakugara/) for more detailed information.

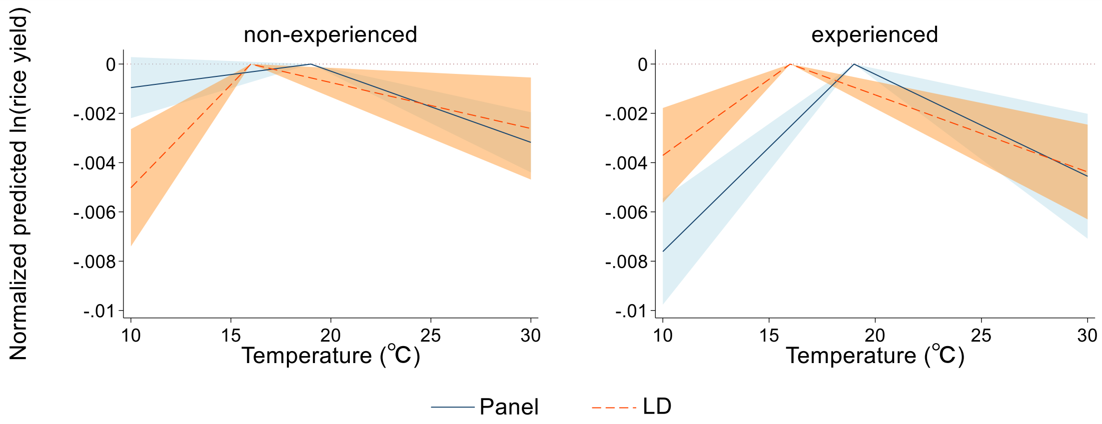

Figure 7. Relationship Between Temperature and Rice Yields:
Non-Cold vs Cold Damage Experienced

Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at threshold temperature, as evaluated by the panel (solid) and long differences models (dash) considering whether the farmer has experienced cold damage in 1993 or not. The shaded areas are 95 percent confidence intervals.

The temperature effect is likely to differ across the regions (cool and warm regions). For instance, northern Japan (relatively cold temperature area) and southern Japan (relatively hot temperature area) may have a different response to temperatures. Thus, we additionally evaluate the regional temperature impacts on rice yields by using the cross-terms of GDD variables with the dummy variable to separate the study cities into the cool and warm regions. We obtain similar results to the previous ones and find additional evidence that the negative impact of temperature beyond the threshold in warm regions is smaller than that in cool regions maybe because of more experience of hot temperature (see Appendix Figure A6).

Finely we explore the difference in the temperature effect between high and low yield cities. Cities with relatively higher average rice yield may have better crop management such as mixed farming, extreme temperature-tolerant varieties of seeds, higher soil quality, etc. We define the high-yield cities as cities that average rice yield during the period 1993-2018 is larger than 50% percentiles of the study cities while low-yield cities are those average yield below the 50% percentiles. We set a dummy variable indicating higher productivity group, which equals 1 if the city is in the high-yield group. The results are shown graphically in Figure 8. Point estimates of the extreme temperature effect on yields in both the panel and long differences suggest that cities belonging to the high-yield group have smaller negative impacts of temperature than cities in the low-yield group. This result is likely to indicate that the adaptation capability of higher productivity group is larger than that of lower productivity group.

We provide the evidence that the results of all specifications above are robust when we apply the step function (3-degree Celsius interval) instead of the GDD estimates (See Appendix C).

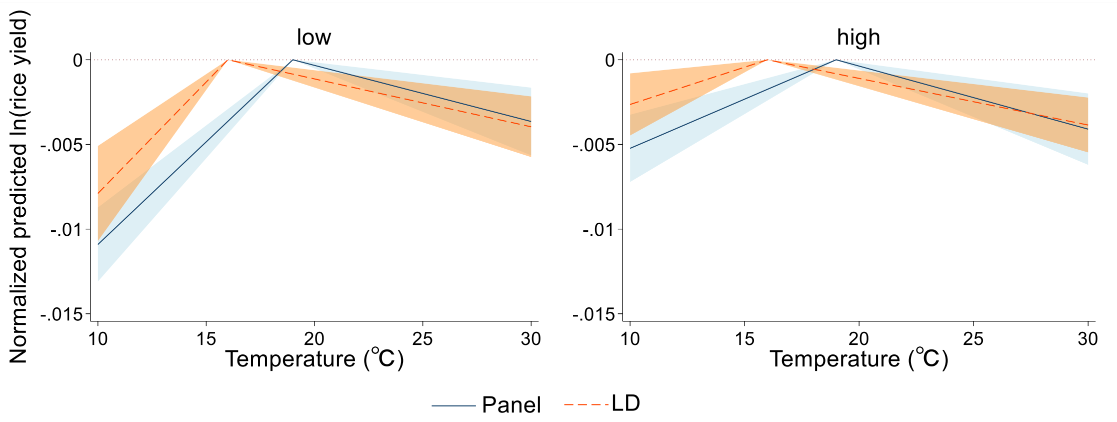

Figure 8. Relationship Between Temperature and Rice Yields: Low vs High Yields

Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at threshold temperature, as evaluated by the panel (solid) and long differences models (dash) considering whether city belongs to low/high yields group or not. The shaded areas are 95 percent confidence intervals.

V. Conclusions

Many studies have explored how climate change affects crop yields, yet none considers the effect of farmer's adaptation capacity on the temperature-yield relationship. Furthermore, most of the studies only focus on either short-term or long-term impacts on yields. We quantify how and to what extent farmer's age and farmer's experience influence the temperature-yield relationship in both the short and long run by conducting panel analysis and long differences approach, respectively.

We find that age and experience are significant factors to strengthen the adaptation capacity of farmers. The experience of the extreme temperature event in the past inspires the magnitude of farmer adaptation to the climate. Age appears to have declining marginal benefits to the temperature-yield link and has been more instrumental to support farmers adjust to annual weather variation than to aid the long-term adaptation to the climate. Farmers aged above 61 years old become susceptible to extreme temperatures in the short run, while the most resilient age is 55 years old in the long run. This gap indicates that the younger generation is likely to enhance their capabilities to adjust to the climate relative to elder farmers. We also find that farms with higher productivity are more resilient to extreme temperatures.

These findings can give us useful policy insights to avoid the further loss of crop yields under the aging farm community. Successful transition to the younger generation is ideal but difficult where the society also suffers from fertility crisis. Alternatively, a key to augmenting the adaptation capacity is education and consolidation. Pertinent knowledge about the weather/climate risk as well as new technologies can help elderly farmers adapt. As such, extension services will play a more salient role in communicating with elderly farmers. In addition, a successful takeover of farmland to more productive farmers can make the farm community more resilient to climate change.

Aging of the farming population also arises in other countries such as the US and Europe. According to the US Censuses of Agriculture, the average age of all U.S. farm principal operators in 2017 was 59.4 years, up 9.1 years from 1978. In the EU only 11% of farmers were under the age of 40 in the latest statistics[20]. Similar to Japan, further aging in the farm society could reduce crop yields. Understanding the adaptation capacity of farmers is an urgent agenda in these countries.

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[20] See Statistics of "Farm indicators by agricultural area, type of farm, standard output, sex and age of the manager and NUTS 2 regions" by Eurostat (https://ec.europa.eu/eurostat/databrowser/view/ef_m_farmang/default/table?lang=en) for more detailed information.

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Appendix

Appendix A

Table A1—Temperature thresholds (Panel)

	15°C	16°C	17°C	18°C	19°C	20°C	21°C
RSS	442.04	440.24	437.81	435.78	435.09	435.84	437.36

Table A2—Temperature thresholds (LD)

	15°C	16°C	17°C	18°C	19°C	20°C	21°C
RSS	0.9320	0.9286	0.9293	0.9346	0.9448	0.9549	0.9632

Table A3—Multi-year average for LD

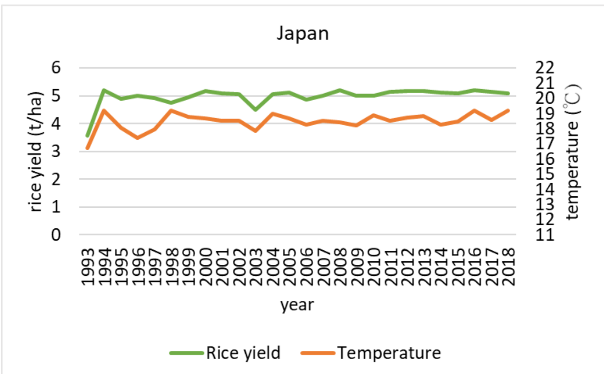
1st Period	1993-1997	1993-1998	1993-1999	1993-2000	1993-2001	1993-2002
2nd Period	2014-2018	2013-2018	2012-2018	2011-2018	2010-2018	2009-2018
RSS	1.7778	1.5531	1.2822	1.0637	1.0161	0.9286

Table A4—Percentage of short-term impacts offset by long-term adaptation

	GDD below threshold	GDD above threshold
β^{short}	0.0008***	-0.0004***
[N=36,713]	(0.0001)	(0.0001)
β^{long}	-0.0006***	-0.0003***
[N=1,384]	(0.0002)	(0.0001)
1- $(\beta^{long}/\beta^{short}) \times 100$	19.74	28.56
	(22.66)	(22.55)

Figure A1. Trend of rice yield and daily average temperature: General vs. regional

General



Regional


Hokkaido
Tohoku
Kanto
Chubu
Kansai
Chugoku
Shikoku
Kyushu
rice yield (t/ha)
temperature (℃)
year
Rice yield
Temperature

Figure A2. Definition of regions of Japan (Blue: Hokkaido; light blue: Tohoku; green: Kanto; light green: Chubu; grey: Kansai; yellow: Chugoku; orange: Shikoku; red: Kyushu)

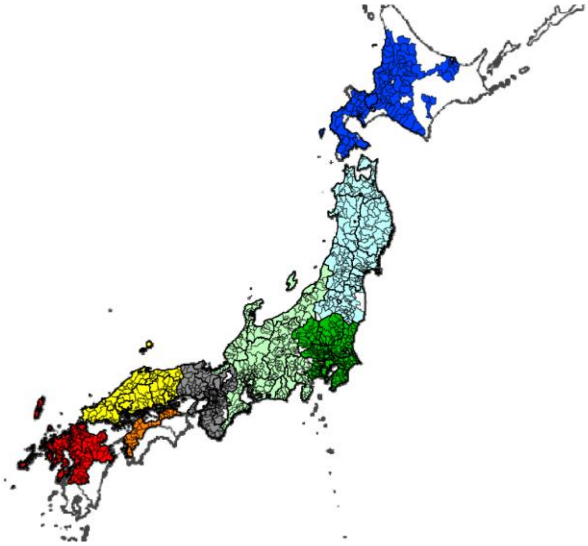
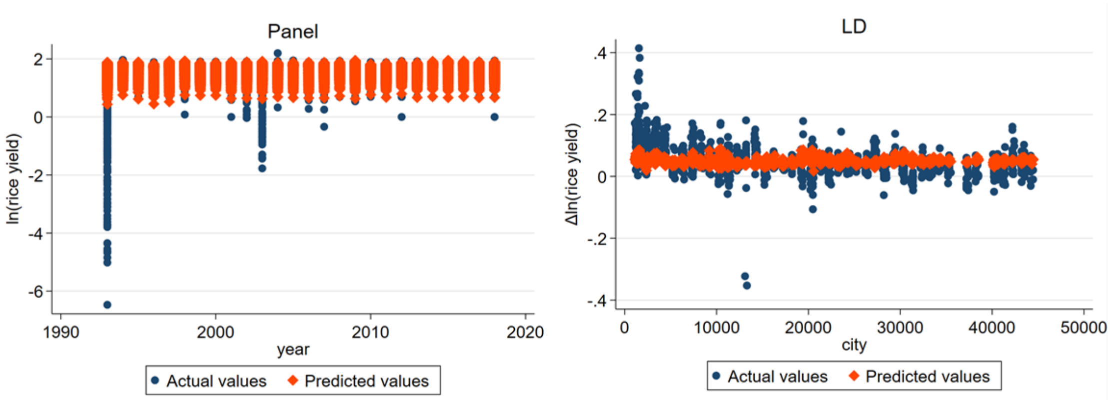
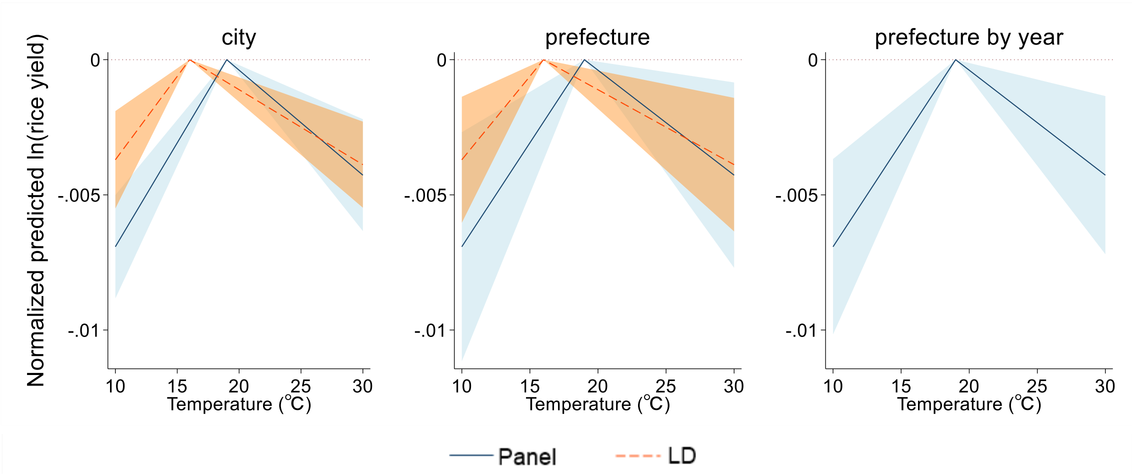


Figure A3. Model performance: Predicted vs. actual values



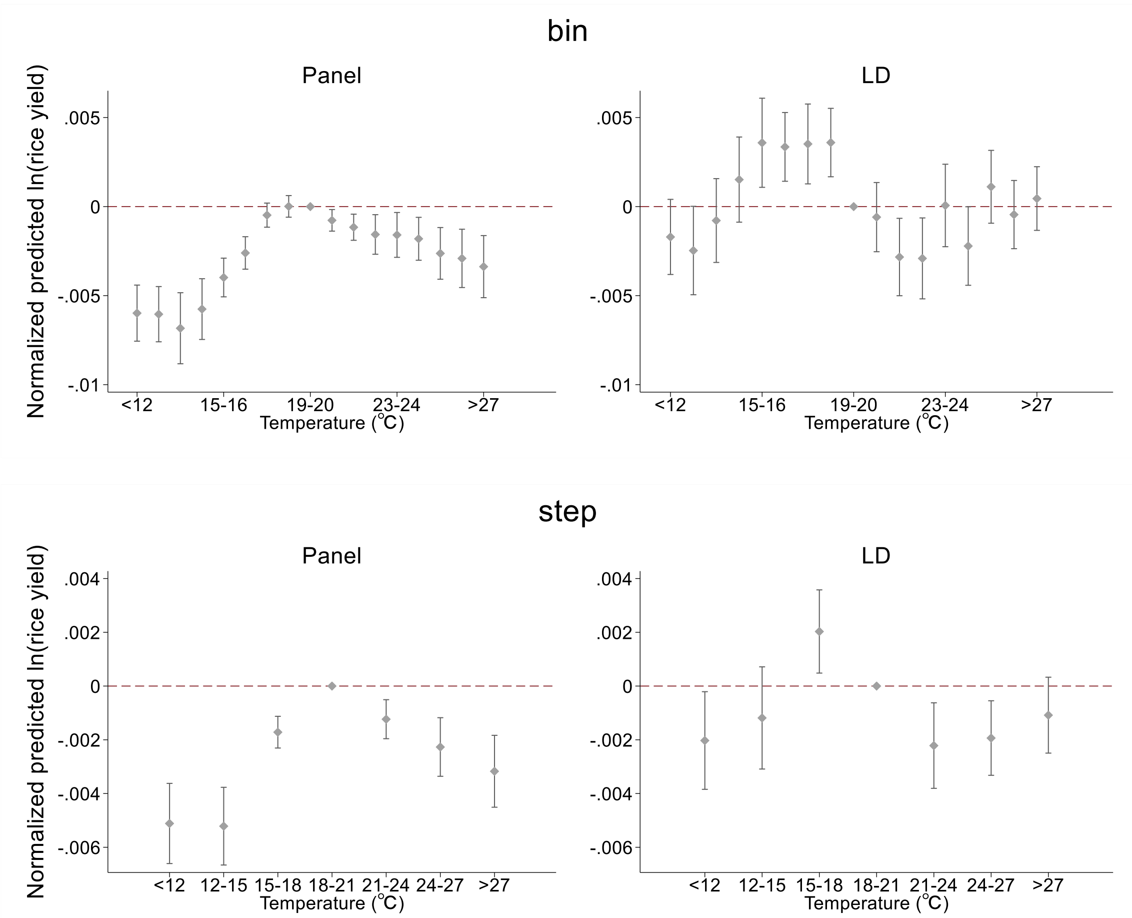
Note: Estimation results are obtained by using column 1 and 3 in Table 2.

Figure A4. Robustness check: Cluster standard error at the different level



Note: Estimation results are obtained by using column 1 and 3 in Table 2.

Figure A5. Robustness check: Model selections



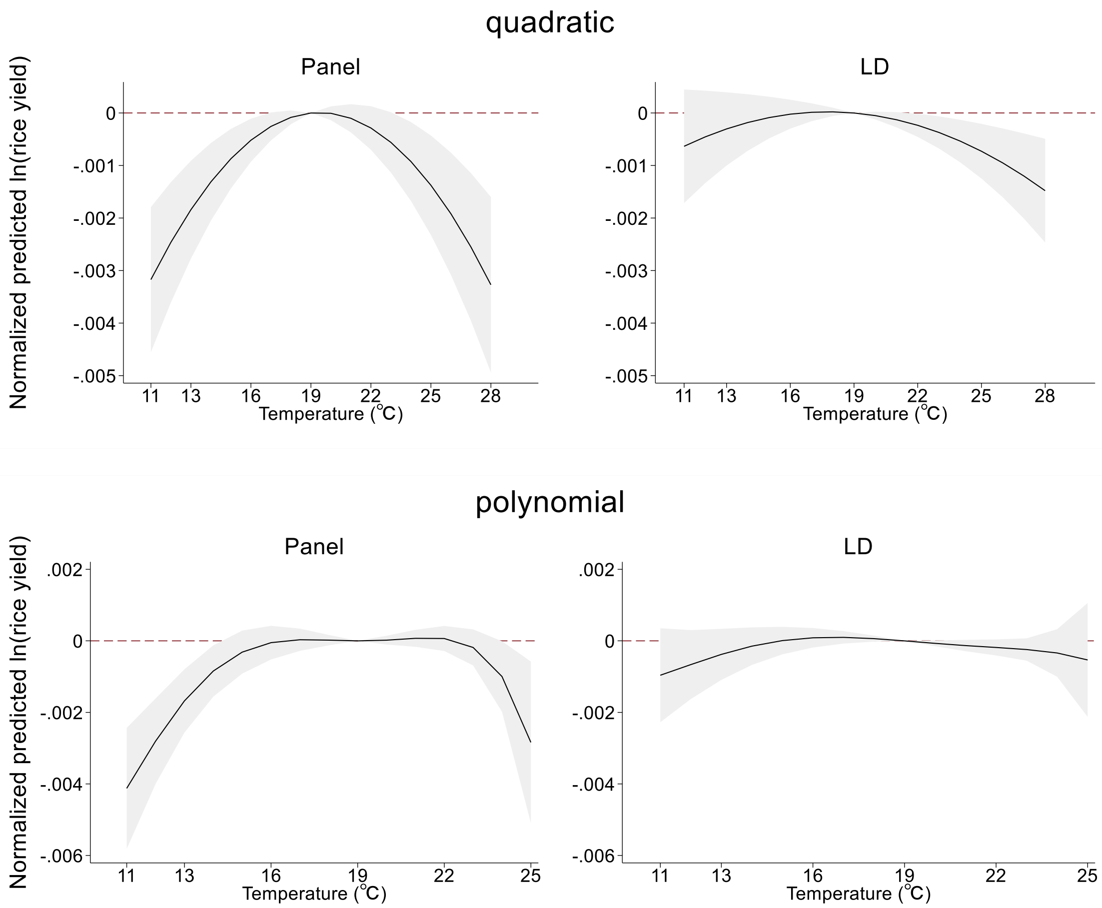
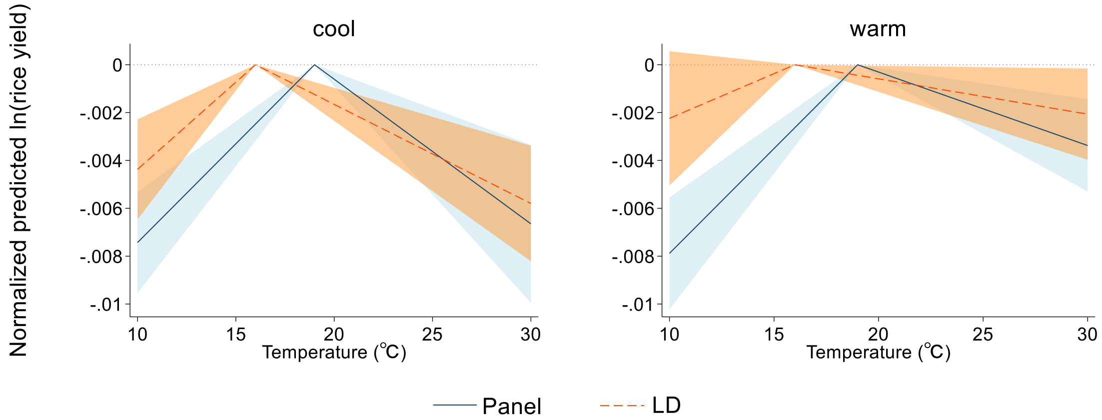
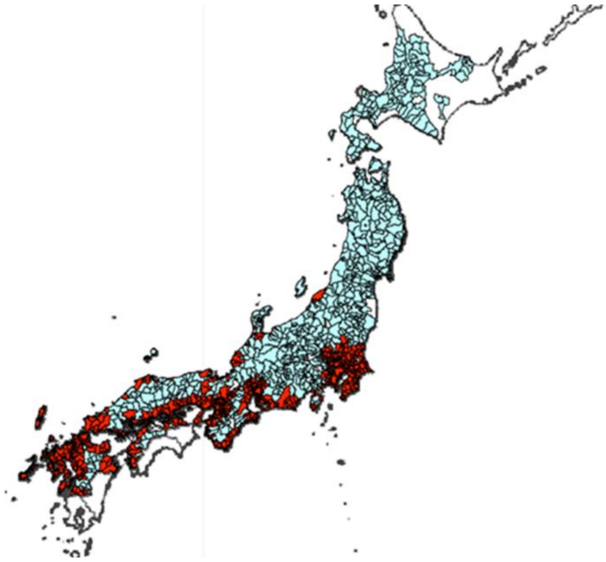


Figure A6. Robustness check: Cool vs. warm regions



Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at threshold temperature, as evaluated by the panel (solid) and long differences models (dash) considering whether city belongs to cool (average daily mean temperature ≤ 19.26°C)/ warm (> 19.26℃) region or not. The shaded areas are 95 percent confidence intervals.

Figure A7. Definition of cool/warm parts of Japan (Blue: cool; Red: warm)



Appendix B

Table B1—Panel and long differences estimates of the impacts of temperature on rice yields

	Panel	Panel	LD	LD
	(1)	(2)	(3)	(4)
GDD 0-18℃	0.0105***	0.0106***	0.0028	0.0037***
	(0.0022)	(0.0021)	(0.0019)	(0.0014)
GDD 18-24℃	-0.0004	-0.0004	0.0004	0.0005
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
GDD above 24℃	-0.0007**	-0.0007**	-0.0007*	-0.0004
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Precip	-0.0032***	-0.0028***	-0.0005	0.0064*
	(0.0011)	(0.0010)	(0.0037)	(0.0034)
Precip^2	0.0001***	0.0001***	0.00003	-0.0003
	(0.00003)	(0.00003)	(0.0002)	(0.0002)
Radiation	0.0457***	0.0454***	0.0471***	0.0274*
	(0.0137)	(0.0137)	(0.0176)	(0.0163)
Radiation^2	-0.0012***	-0.0012***	-0.0013***	-0.0007
	(0.0004)	(0.0004)	(0.0005)	(0.0004)
Obs.	36,713	36,713	1,384	1,384
FE	City, Pref-Year	City, Pref-Year	Prefecture	Prefecture
Control var.	No	Yes	No	Yes
Adj. R^2	0.6835	0.6855	0.5739	0.6221
F statistic	14.56	8.28	2.39	3.39

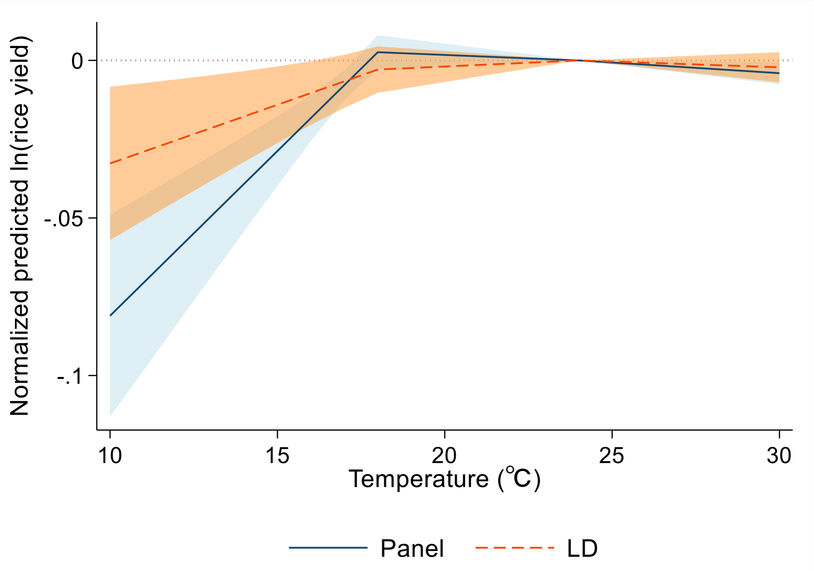
Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. Columns 1-2 are estimated with an annual panel, and 3-4 with long differences, and all use thresholds as selected by the panel model. Columns 1 and 3 are our baseline models for panel and long differences, respectively. Columns 2 and 4 are estimated with additional control variables shown at the bottom; see main text for details. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

Table B2–Effect of adaptation capacity of farmer's age

	Panel	LD
	(1)	(2)
GDD 0-18℃	0.5589	0.2391
	(0.4018)	(0.2490)
GDD 0-18℃ × age	-0.0178	-0.0078
	(0.0139)	(0.0088)
GDD 0-18℃ × age^2	0.00014	0.00006
	(0.00012)	(0.00008)
GDD 18-24℃	0.0233	0.0098
	(0.0371)	(0.0332)
GDD 18-24℃ × age	-0.00084	-0.00033
	(0.0013)	(0.0012)
GDD 18-24℃ × age^2	0.0000075	0.0000029
	(0.0000110)	(0.0000102)
GDD above 24℃	-0.0125	-0.0111
	(0.0165)	(0.0217)
GDD above 24℃ × age	0.00042	0.00038
	(0.00057)	(0.00076)
GDD above 24℃ × age^2	-0.0000037	-0.0000033
	(0.0000049)	(0.0000066)
Obs.	36,713	1,384
FE	City, Prefecture-Year	Prefecture
Adj. R^2	0.6885	0.6000
F statistic	8.09	2.26
Threshold age	56-64	57-65

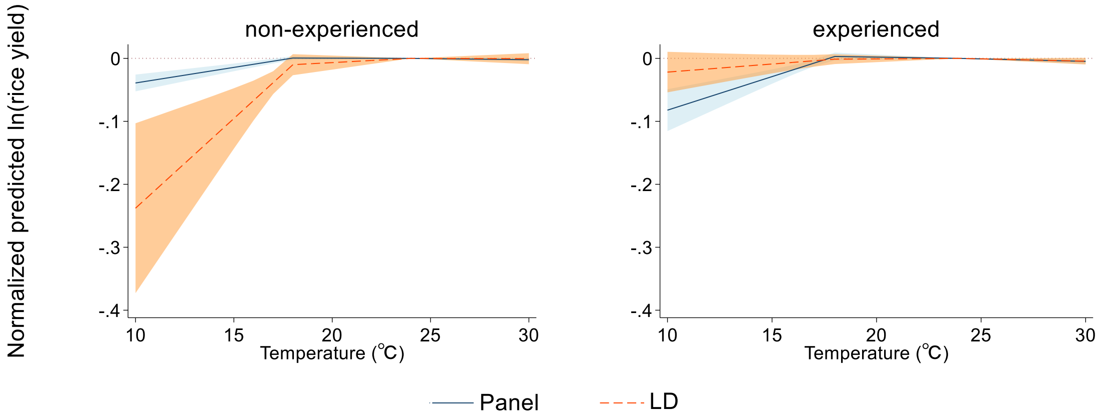
Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. Both estimations include single and square terms of precipitation, global solar radiation, and age. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors (se) clustered at the city level are reported in parentheses (bootstrap wild se for LD, replications 1,000 times). Regressions are weighted by the 1993–2018 average rice planted area.

Figure B1. Relationship between temperature and rice yields



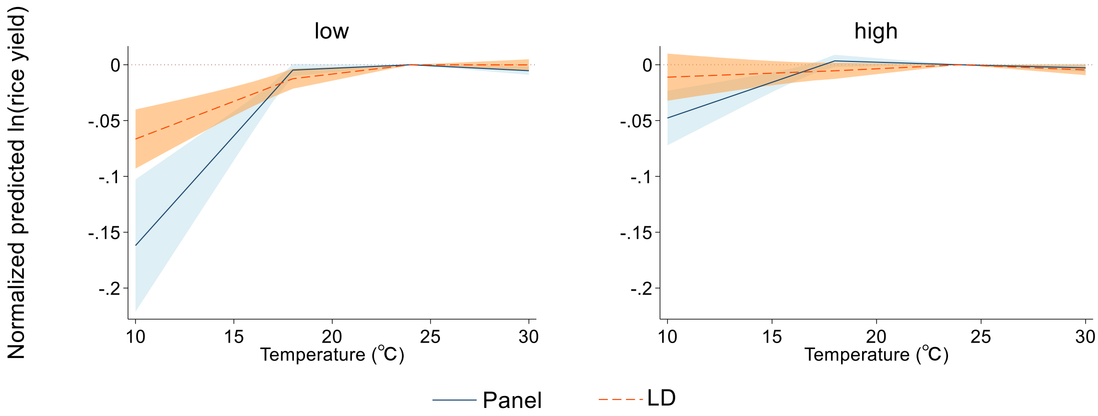
Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at 24°C, as evaluated by the panel (solid) and long differences models (dash). The shaded areas are 95 percent confidence intervals.

Figure B2. Relationship between temperature and rice yields: Non-cold vs cold damage experienced



Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at 24°C, as evaluated by the panel (solid) and long differences models (dash) considering whether the farmer has experienced cold damage in 1993 or not. The shaded areas are 95 percent confidence intervals.

Figure B3. Relationship between temperature and rice yields: Low vs high yields



Notes: Estimates display the change in ln rice yield under an extra day of exposure to a given °C temperature relative to a day spent at 24°C, as evaluated by the panel (solid) and long differences models (dash) considering whether city belongs to low/high yields group or not. The shaded areas are 95 percent confidence intervals.

Appendix C

Table C1 —Summary statistics (3-degree Celsius interval)

Temperature bin (°C)	Obs.	Mean	SD	Min	Max
<12	36,713	31.20	27.23	0	154
12-15	36,713	26.32	9.95	0	67
15-18	36,713	36.97	8.39	11	74
18-21	36,713	41.21	9.09	1	76
21-24	36,713	36.12	12.75	0	83
24-27	36,713	28.31	17.68	0	79
>27	36,713	13.86	16.73	0	71

Notes: The unit of each value (except observation) is the average number of days during the growing season (Apr. to Oct.) 1993-2018.

Table C1 indicates the summary statistics of temperature bins. Nearly 37 days during the growing season (214 days) that the daily mean temperature is between 15-18°C and around 41 days is between 18-21°C. In addition, approximately 14 days during the growing period that rice is suffering from extremely high daily mean temperature.

Our baseline regression model (step function) for panel approach (short-term impact) is as follow:

$$ln\, y_{it} = \sum_{q=1}^{Q} \alpha_q\, N\_temp_{iqt} + \sum_{m=1}^{M} \beta_m\, N\_prec_{imt} + \delta_1 gsr_{it} + \delta_2 gsr_{it}^2 + \gamma_i + \theta_{pt} + \varepsilon_{it},$$

where y_{it} is the rice yield in the city i in year t, N_temp_{qit} measures the number of days in q^{th} temperature bin, N_prec_{mit} gives the number of days in m^{th} precipitation bin, and gsr_{it} average daily global solar radiation. Importantly, γ_i, the city fixed effect, and θ_{pt}, prefecture by year fixed effects, are also included. ε_{it} indicates the error term. The temperature bins used in this study are temperature below 12℃, 12-15℃, 15-18℃, 18-21℃ (our base temperature bin), 21-24℃, 24-27℃ and above 27℃. The precipitation bins are set up for precipitation below 20mm (our base precipitation bin), 20-60mm, 60-100mm, 100-200mm, 200-300mm, and above 300mm. We employ the square term of global solar radiation for simplification.

Our main panel estimations for rice yield using step function are presented in Table C2. Model 1 is our baseline model. In Model 2 we use year fixed effect instead of prefecture by year effect, and in Model 3 we use the single and square terms of average daily mean precipitation in place of the precipitation bins for simplicity and to check up on the multicollinearity. In Model 4 we add the control variables, due to the availability of the data, we use the general farmer information of the number of farm households per total cultivated land area, single and square terms of farmers' average age, percentage of full-time farm household[21] and percentage of business farm household[22] and we use rice farmer information of rice transplanters per rice planted area and rice planted land area per rice farm household.

We obtain the same results for all models, though the results of Model 2 are slightly larger in absolute value. This occurs because in Model 2 we do not control the year effect by prefecture, suggesting the existence of heterogeneity at the prefecture-level that varies across years. Compare with our base temperature bin, 18-21℃, we find the negative responsiveness of rice yield to the temperature below 18℃and temperature above 21℃. Moreover, exposure to temperatures below 18℃ and temperatures above 21℃ has sharp declines in rice yield, which indicates an inverted U-shaped link. In our base specification, exposure to one additional day of colds below 12℃ results in a decline in overall rice yield of 0.51 percent, and a -0.52 percent yield decrease for an

[21] Number of general full-time farm households/ Total number of general farm households
[22] Number of general business farm households/ Total number of general farm households

Table C2—Panel estimates of the impacts of temperature on Japan rice yields

	ln (Rice Yield)			
	Model (1)	Model (2)	Model (3)	Model (4)
<12°C	-0.0051***	-0.0061***	-0.0051***	-0.0052***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
12-15°C	-0.0052***	-0.0058***	-0.0052***	-0.0052***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
15-18°C	-0.0017***	-0.0046***	-0.0017***	-0.0017***
	(0.0003)	(0.0005)	(0.0003)	(0.0003)
21-24°C	-0.0012***	-0.0011***	-0.0012***	-0.0012***
	(0.0004)	(0.0002)	(0.0004)	(0.0004)
24-27°C	-0.0023***	-0.0033***	-0.0023***	-0.0022***
	(0.0006)	(0.0004)	(0.0006)	(0.0006)
>27°C	-0.0032***	-0.0055***	-0.0032***	-0.0031***
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
Observations	36,713	36,713	36,713	36,713
Fixed effects	City, Pref-Year	City, Year	City, Pref-Year	City, Pref-Year
Precipitation	Bins	Bins	Single, Square	Bins
Control var	No	No	No	Yes
Adj R-squared	0.6823	0.4128	0.6822	0.6837
F statistic	9.06	18.40	10.79	6.70

Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. Model 1 is our baseline model and Model 2-4 are estimated with different fixed effects, the form of precipitation, and control variables shown at the bottom; see text for details. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

extra day of temperature between 12-15°C. For the hot temperatures, one more day of temperature among 24-27°C brings about a 0.23 percent reduction in rice productivity and a -0.32 percent productivity diminution for an added day of heat above 27°C. From these results, we notice that rice yield in Japan is more vulnerable to cold temperatures, which is consistent with the results from quantity estimates in Kawasaki and Uchida (2016). Cold damage has been a serious problem especially in the northern part of Japan, which causes the inhibition of pollen formation and sterility (fertilization disorder) of rice. We interpret that the parameters of lower temperature bins capture such cold damage.

The long-term regression model is as follow:

$$\Delta \ln y_i \;=\; \sum_{q=1}^{Q} \alpha_q \, \Delta N\_temp_{iq} \;+\; \sum_{m=1}^{M} \beta_m \, \Delta N\_prec_{im}$$
$$+\; \delta_1 \, \Delta gsr_i \;+\; \delta_2 \, \Delta gsr_i^2 \;+\; \lambda_p \;+\; \Delta\varepsilon_i,$$

where Δy_i is the first difference in rice yield in the city i between a and b periods, a and b periods are calculated by using the multi-year average, take the 10-year average, for example, period a represents the 10-year average over 1993-2002 and period b indicates 10-year average over 2009-2018. ΔN_temp_{iq} shows the change in q^{th} temperature bin between two periods. ΔN_prec_{im} presents the difference in m^{th} precipitation bin and Δgsr_i the difference in average daily global solar radiation. Additionally, we control the unobservable variable that does not vary over time within each prefecture (λ_p) in the regression model.

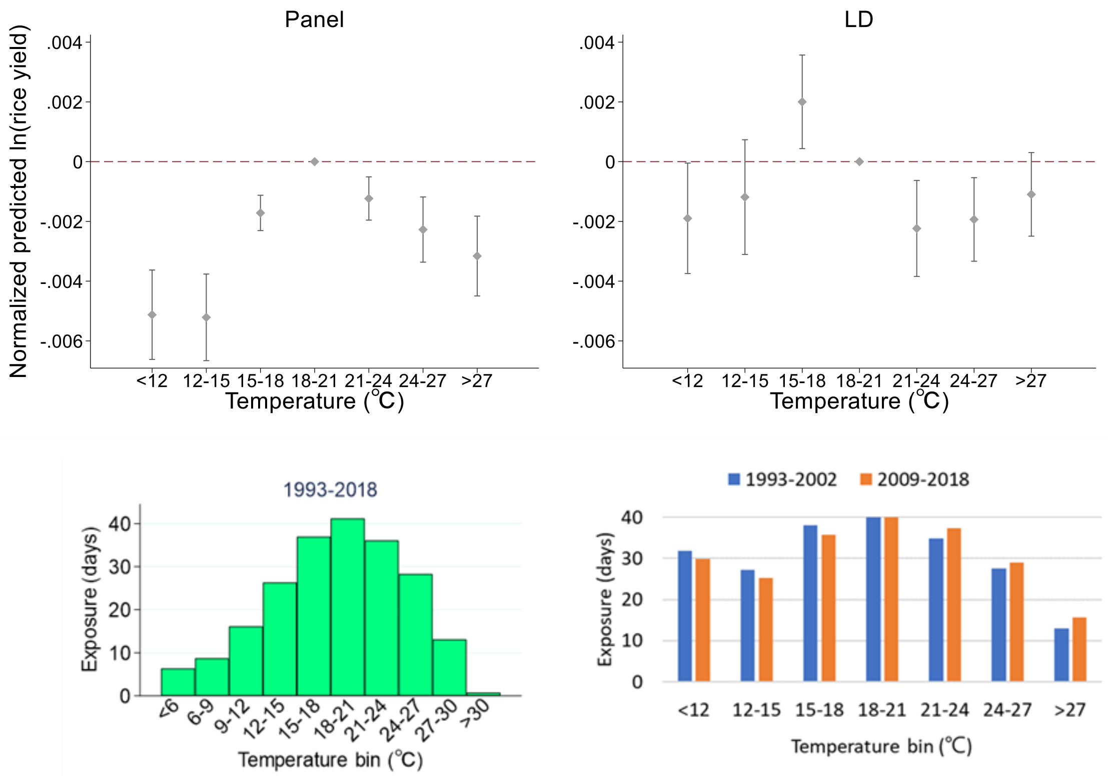
In Table C3, we provide the main estimation under the long differences approach. Columns 1-6 are the differences between the 1993-1997 and 2014-2018 periods (5-year average), 1993-1998 and 2013-2018 periods (6-year average), 1993-1999 and 2012-2018 periods (7-year average), 1993-2000 and 2011-2018 periods (8-year average), 1993-2001 and 2010-2018 periods (9-year average), 1993-2002 and 2009-2018 periods (10-year average), respectively. We change the average of years of two periods to test the robustness of the long-term rice yield results. We find the negative responsiveness of yield to temperatures below 15℃ and temperatures above 21℃ relate to our base temperature bin, 18-21℃. The long-term estimation results are quite compatible across all 6 models. We select the 10-year average result for interpretation as it has the smallest sum of square residuals among the models. In our long-term specification, we denote that exposure to each additional day of colds below 12℃ causes a loss in rice yield of 0.19 percent, which is 0.32 percent less in negative point estimate than when we apply the panel approach. By comparing the panel and the long differences results, we indicate that relative to our base temperature bin, the negative sensitivity of rice yield to the temperature below 18℃ and temperature above 24℃ becomes lesser in the long-term analysis. Farmer's adaptations appear to alleviate the negative temperature impact on rice yield in the long run. The graphical results of the panel and long differences estimations are shown in Figure C1 (we take Model 1 in Table C2 and Column 6 in Table C3 for comparison).

Table C3—Long differences estimates of the impacts of temperature on Japan rice yields

	ln (Rice Yield)					
1st Period	1993-1997	1993-1998	1993-1999	1993-2000	1993-2001	1993-2002
2nd Period	2014-2018	2013-2018	2012-2018	2011-2018	2010-2018	2009-2018
	(1)	(2)	(3)	(4)	(5)	(6)
<12℃	-0.0023**	-0.0017	-0.0015	-0.0022**	-0.0018*	-0.0019**
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0010)	(0.0009)
12-15℃	-0.0019**	-0.0017**	-0.0018**	-0.0018**	-0.0022**	-0.0012
	(0.0008)	(0.0007)	(0.0009)	(0.0009)	(0.0010)	(0.0010)
15-18℃	0.0021***	0.0024***	0.0016**	0.0017**	0.0014	0.0020**
	(0.0007)	(0.0006)	(0.0007)	(0.0008)	(0.0009)	(0.0008)
21-24℃	-0.0015**	-0.0023***	-0.0022***	-0.0023***	-0.0019**	-0.0022***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
24-27℃	-0.0015**	-0.0016**	-0.0026***	-0.0024***	-0.0024***	-0.0019***
	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
>27℃	-0.0017*	-0.0008	-0.0015*	-0.0019**	-0.0019***	-0.0011
	(0.0009)	(0.0009)	(0.0008)	(0.0008)	(0.0007)	(0.0007)
Observations	1,384	1,384	1,384	1,384	1,384	1,384
Fixed effects	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture	Prefecture
Adj R-squared	0.6805	0.6644	0.6227	0.6158	0.6110	0.5906
F statistic	7.49	6.98	4.05	3.59	3.11	2.98

Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. The two periods of specifications 1-6 are calculated by different multi-year averages shown at the top; see main text for details. All estimations include the first difference of the precipitation bins, the single and square terms of global solar radiation between two periods. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

Figure C1. Relationship between temperature and rice yields



Notes: Estimates display the change in ln rice yields under an additional day of exposure to a given temperature interval relative to one day spent at the base temperature bin, 18-21°C. Lines are 95 percent confidence intervals and circles are point estimates. Histograms at the bottom of each frame indicate the average temperature exposure among all study cities in the data.

In Table C4 and Table C5, the first column indicates the coefficient of each temperature bin without interaction, the second and third columns are the coefficient of each bin interacted with age and age-squared, respectively. In both panel and long differences-specifications, the results of cross-terms of farmers' age display that farmers' age have an inverted U-shaped connection with rice yields, the threshold that maximizes yields is 60-62 years old in panel analysis and 56-60 years old in long differences approach. The average farmers' age in the study cities during the analytical period is 57 years old, which implies that many cities have enough capability to minimize the cold and hot damages. However, once the farmers' age exceeds the threshold ages, the farmers' adaptation capability is decreased. Note that the threshold age is 3 years younger in the long-term analysis, implying that younger farmers are more capable to alleviate the losses under the extreme temperature in the long- run (younger farmers may gain the experiences, learn, and adopt new technology, etc.). We present the graphical results of both short- and long-terms temperature effects on yields under three age scenarios in Figure C2, and our two main findings are as follows: (1) Farmer age of 60 has the best responsiveness to temperatures compared with farmer age of 50 and 70 in both short- and long-term analysis. (2) Compare with the base temperature bin, younger farmers appear to have a lesser negative sensitivity of temperature in the long run while we do not see the same advance in elder farmers, suggesting that younger farmers are likely to increase the capability to mitigate the negative temperature impact on yield in the long-term.

Table C4 – Effect of adaptation capability of farmer's age (Panel)

	Temperature bin	Temperature bin X Age	Temperature bin X Age-squared
<12℃	-0.1516*	0.0048*	-0.00004*
	(0.0783)	(0.0026)	(0.00002)
12-15℃	-0.4375***	0.0143***	-0.00012***
	(0.1510)	(0.0051)	(0.00004)
15-18℃	-0.2649**	0.0088**	-0.00007**
	(0.1204)	(0.0042)	(0.00004)
21-24℃	-0.0330	0.0009	-0.00001
	(0.0662)	(0.0022)	(0.00002)
24-27℃	-0.1582**	0.0051**	-0.00004**
	(0.0730)	(0.0025)	(0.00002)
>27℃	-0.2692**	0.0088**	-0.00007**
	(0.1077)	(0.0036)	(0.00003)
Observations	36,713		
Fixed effects	City, Pref-Year		
Adj R-squared	0.6874		
F statistic	5.18		

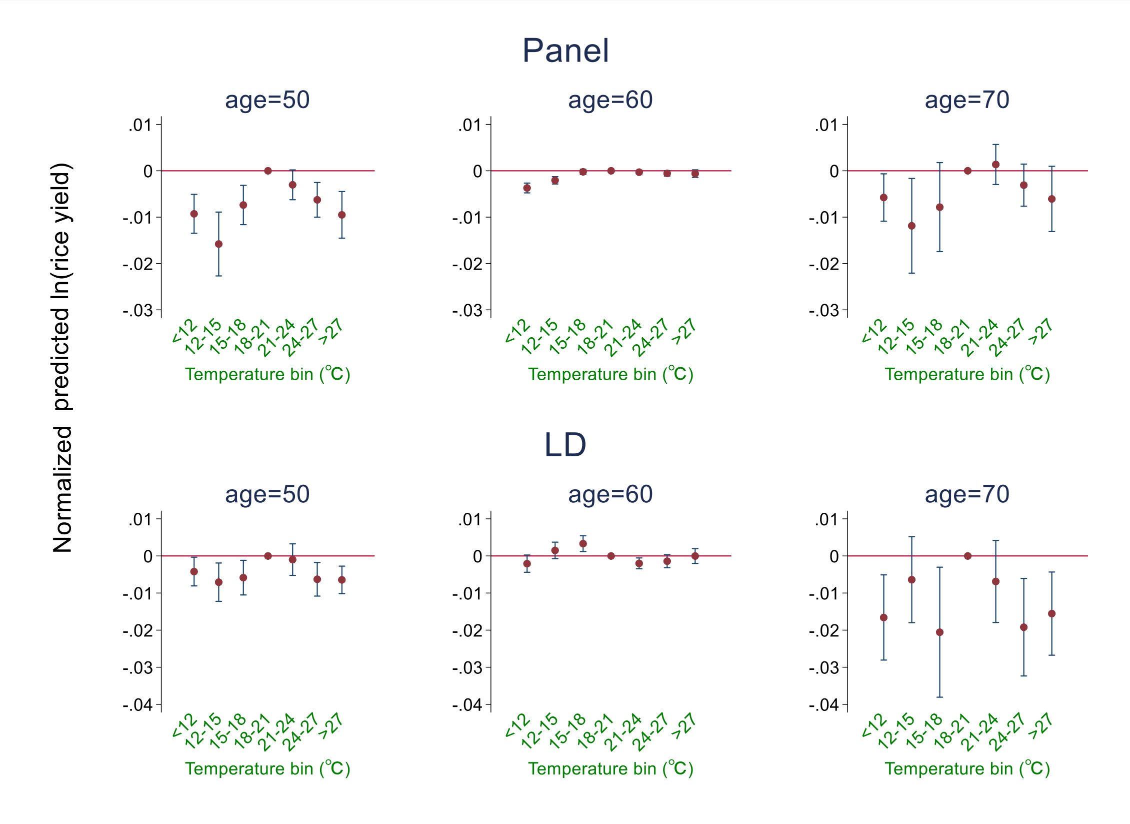
Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. The estimation includes precipitation bins, single and square terms of global solar radiation and age. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

Table C5 – Effect of adaptation capability of farmer's age (LD)

	Temperature bin	Temperature bin X Age	Temperature bin X Age-squared
<12℃	-0.2645**	0.0094**	-0.00008**
	(0.1122)	(0.0039)	(0.00003)
12-15℃	-0.2967**	0.0099**	-0.00008**
	(0.1302)	(0.0045)	(0.00004)
15-18℃	-0.5469***	0.0191***	-0.00017***
	(0.1696)	(0.0060)	(0.00005)
21-24℃	-0.0541	0.0020	-0.00002
	(0.1161)	(0.0040)	(0.00004)
24-27℃	-0.3708***	0.0130***	-0.00011***
	(0.1349)	(0.0047)	(0.00004)
>27℃	-0.3679***	0.0127***	-0.00011***
	(0.1149)	(0.0040)	(0.00004)
Observations	1,384		
Fixed effects	Prefecture		
Adj R-squared	0.6238		
F statistic	2.92		

Notes: ***, ** and * denote 1%, 5% and 10% significant level, respectively. The estimation includes the first difference of the precipitation bins, the single and square terms of global solar radiation and age between two periods. Data are for Japan single cropping cities which continuously produce rice, 1993-2018. Standard errors clustered at the city level are reported in parentheses. Regressions are weighted by the 1993–2018 average rice planted area.

Figure C2. Relationship between age-temperature and rice yields

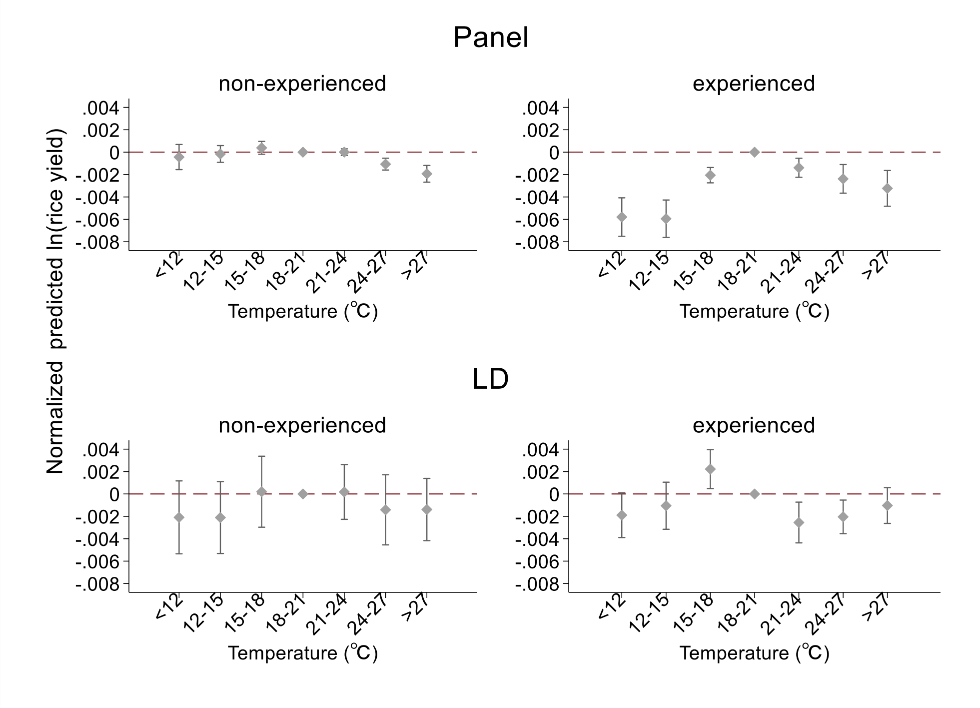


Notes: Estimates display the change in ln rice yields under an additional day of exposure to a given temperature interval relative to one day spent at the base temperature bin, 18-21℃. Lines are 95 percent confidence intervals and circles are point estimates.

In Figure C3, we find that farmers in prefectures that suffered from the cold damage in the year 1993 tend to reduce the negative cold temperature effects in the long run which we do not observe the identical breakthrough in farmers in prefectures with no cold damage experience in the year 1993.

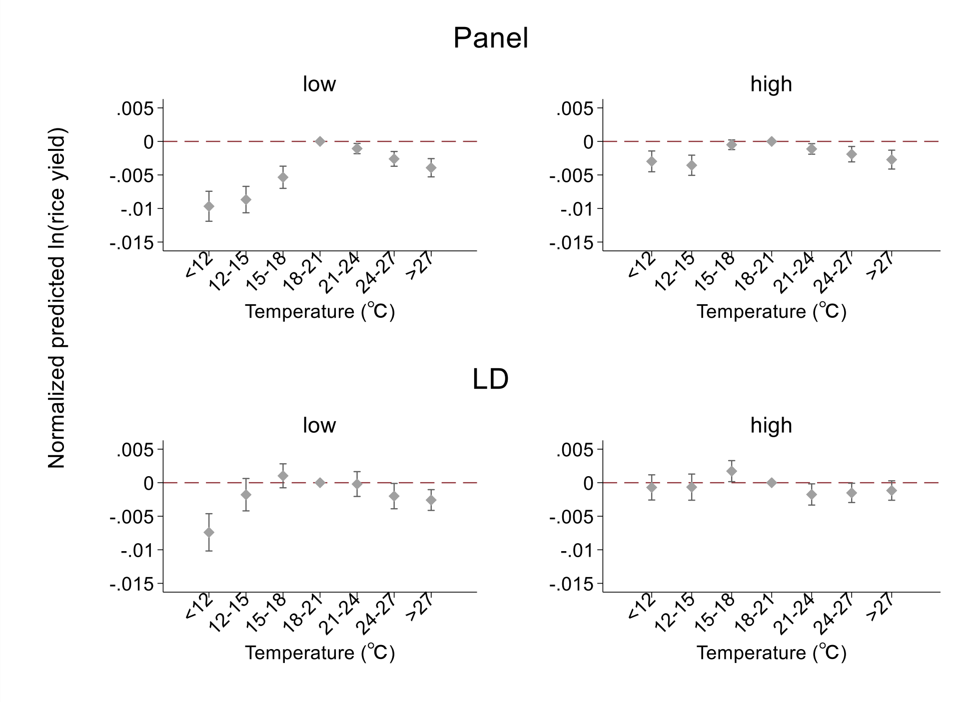
In Figure C4, point estimates of the extreme temperature effect on yield in both panel and long differences approaches suggest that cities belonging to the high-yield group have a better productivity response to temperature relative to cities in the low-yield group.

Figure C3. Relationship between temperature and rice yields: Cold vs no cold damage experiences



Notes: See *Notes* in Figure C2.

Figure C4. Relationship between temperature and rice yields: High vs low yields



Notes: See *Notes* in Figure C2.

Figure C5. Model performance: Predicted vs. actual values

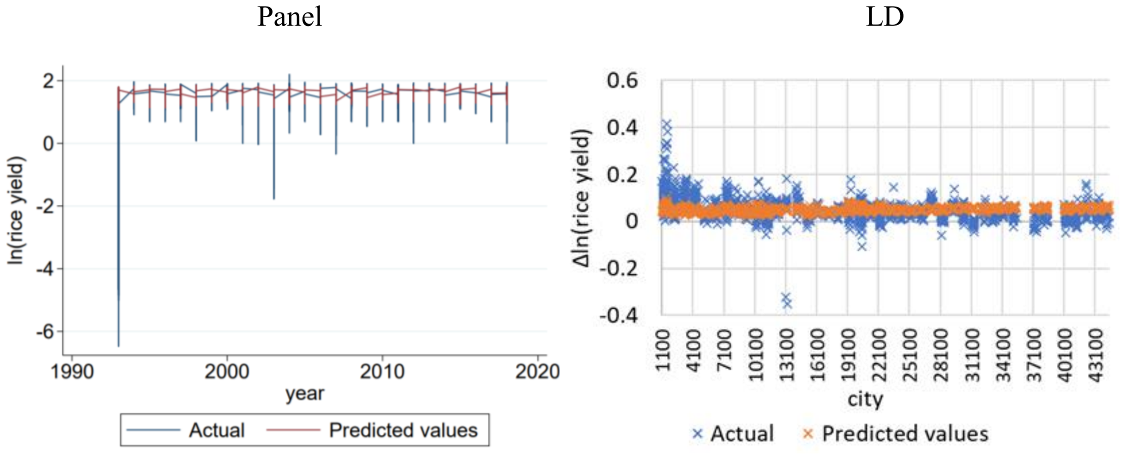


Figure C6. Robustness check: Cluster standard error at the different level