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Aging Farmers and the Role of Community in Adaptation to Extreme Temperature Effects on Crop Yields: Empirical Evidence from Japan[†]

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Abstract

This study explores farmer's adaptation mechanisms to climate change. We explore how farmer's age and engagement in community activities affect crop production under extreme temperatures. By using the municipality-level data on Japanese rice production in 2001–2018, we find a nonlinear (inverted U-shaped) age effect on the relationship between temperatures and rice yields. Farmers aged 60 exhibit the most capable of mitigating yield losses from extreme temperatures, while farmers above and below this age threshold suffer significant yield declines. Such declines can be averted by reinforcing networks and relationships among farm community members through active engagement in the community.

Keywords: Age, Climate change, Crop yields, Extreme temperatures, Farm community engagement, Farmers' adaptation capability, Rice

JEL classification: Q10, Q51, Q54

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I. Introduction

Population aging in mature societies shows no signs of stopping. The share of older cohorts in the population continues to increase in most OECD countries (Daniele, et al. 2020). Japan is one of the fastest aging societies among them, with the aging population rate (proportion of people aged 65 and older) of nearly 30 percent as of 2021. The agricultural sector has led this trend to another level. In particular, the aging rate of rice farmers has reached over 70 percent according to the 2020 Agricultural Census.

Such abnormal aging of farmers can make them susceptible to extreme temperatures under the rapid progression of global warming in recent years. This can stem from their limited adaptation capability to the changing environment. Recently, heat-oriented reductions in crop yields and quality have been reported worldwide (e.g., Schlenker and Roberts 2009; Burke and Emerick 2016; Chen et al. 2016; Kawasaki and Uchida 2016; Aragón et al. 2021). To mitigate the crop damage, adoption of adaptive technologies and practices has been encouraged by governments and local authorities, such as introduction of heat-resistant varieties, crop conversion, changes in planting seasons, and ICT technologies for production environment control. Whereas many adaptive technologies and practices are available to farmers, their adoption in the field depends on their management skills and incentives.

Generally, as age increases, physical and cognitive abilities decline, making it difficult to adapt to new environmental changes (Barnes et al. 2019; Shang et al. 2021). Elderly farmers approaching retirement have little incentive to invest in costly new technologies. Consequently, the decline in physical and cognitive functions and the lack of investment incentives lead to a decrease in the ability to adapt to extreme weather.[1] In contrast, aging of young farmers can initially have a positive impact on production, as farmers accumulate valuable experiences and knowledge through learning-by-doing. This can enhance the capability to adapt to warming temperatures.[2]

We incorporate this inverted U-shaped aging–production relationship into the context of crop yield response

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[1] The negative age effect is also highlighted in the economic literature on labor productivity (Maestas et al. 2016; Lee and Shin 2019) and total factor productivity (Park et al. 2021). Park et al. (2021) showed that total factor productivity declines more as the percentage of workers in their 60s increases.
[2] Tamura et al. (2021) found that farmers' experience and the knowledge of adaptation measures are positively correlated with their adaptive behavior.

function to extreme temperatures.[3] Most crops such as corn, soybeans and rice have certain threshold of temperatures for growing, beyond which crop yields significantly decline, shaping the inverted U-shaped temperature–yield relationship (e.g., Schlenker and Roberts 2009; Burke and Emerick 2016; Kawasaki and Uchida 2016). We claim that the degree to which crop yields decline at extreme temperatures can be partly explained by farmers' age, because age can represent the capability to adapt to those negative shocks. That is, aging at an early stage can mitigate the negative temperature effects on crop yields, while aging at a later stage causes the opposite result.

Factors contributing to the decline in the adaptive capability are not limited to the aging of individual farmers. Matured and dysfunctional communities also become vulnerable to external shocks. In healthy farm communities, active involvement of farmers in local gatherings can facilitate farmers' access to valuable social support networks, information resources, learning opportunities, and market insights. These factors collectively serve as strong motivators, encouraging farmers to adapt and modernize their farming technologies and practices as well as to manage common properties such as waterway maintenance for irrigation. Such community engagement significantly enhances farmers' adaptability to climate change (Uddin et al. 2014; Rondhi et al. 2019). This suggests active community participation can buffer the negative effects of aging on crop yields.

In sum, this study explores to what degree farmers' age and local community engagement affect the negative effects of extreme temperatures on crop yields.[4] It is yet unclear in the literature whether the adaptation capability of farmers and farm communities mitigates the negative effects of climate change. Revealing the mechanisms of adaptation to temperature-induced productivity changes is critical consideration for policymakers, particularly in the aging society. Also, embodying adaptation mechanisms in the empirical model can segregate the temperature effect on crop yields from the adaptation effect.

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[3] Such a concave relationship between age and crop productivity has been observed for decades in US agriculture (Tauer 1984; 2017).

[4] Other factors can also determine farmers' adaptation to climate change, such as education, farm size, and access to financial and extension services (e.g., Deressa et al. 2009; Shikuku et al 2017; Kgosikoma et al. 2018). We control for these potential confounding factors in estimation.

We use Japanese rice paddy production for the empirical analysis. Rice is widely cultivated throughout Japan and is highly susceptible to extreme temperatures. As mentioned earlier, the aging rate of Japanese rice farmers is markedly high overall, but it varies across Japan over time. We also observe the level of local community engagement in the different pattern of variations. These spatial and temporal heterogeneities of farmers' age and community engagement level as well as temperatures allow us to examine whether aging and community engagement have a nonnegligible impact on crop production under extreme temperatures.

We employ a rich dataset at the municipality level, covering the years 2001 to 2018, which encompasses specific information on rice yields and farm characteristics.[5] This dataset is combined with daily records of average temperatures, precipitation, and global solar radiation at the gridded level. These precise and extensive weather data enable us to accurately estimate the nonlinear effects of the cumulative heat, precipitation, and radiation experienced by rice production throughout the growing season.

We confirm that the farmers' age largely explains the inverted U-shaped temperature–yield relationship. At an optimal farmer's age of about 60 years old, the gradient of the crop yield response function is effectively flat, exhibiting that crop production is reasonably adapted to extreme cold and warm temperatures, while those below/above this age threshold experience significant yield declines. These findings hold across various specifications. They suggest that too-young and too-old age acts as a barrier to adaptation to extreme temperatures. Simulation results show that rice yields are as much affected by aging as temperature rise, and that combination of them makes rice production further vulnerable. Such a negative age effect can be attenuated in municipalities with highly active engagement of farmers in their communities. This implies that reinforcing networks and relationships among farm community members through community engagement can help beginning and retiring farmers share knowledge and resources with farmers with best practices, and better adapt to the extreme temperatures.

The remainder of this paper is organized as follows: Section II describes the background of Japanese rice production and aging population; Section III explains the empirical methodology and data; Sections IV and V

[5] The size of municipalities in Japan is at microscale, about 214km^2 on average, which is equivalent to US average land area per five-digit ZIP codes.

discuss with estimation results and simulation results, respectively; and Section VI concludes.

II. Background: Rice Production in the Aging Community in Japan

Rice stands as a staple food crop widely cultivated throughout Japan. More than 70 percent of farmers engage in rice farming as a primary crop (Figure A1). Among them, more than 70 percent have reached above 65 years old according to the 2020 Agricultural Census.

Since the early 2000s, hot temperatures have been observed more frequently during the rice growing season in Japan, resulting in adverse effects on rice production (Kawatsu et al. 2007; Okada et al. 2011; Kawasaki and Uchida 2016). Figure 1 presents the change in daily mean temperatures during the growing season over the 2001–2018 period. Temperatures have increased in more than 75 percent of the municipalities over the 18-year span, with a maximum recorded increase of 1 ºC. Figure 2 displays the evolution of rice yields over the same timeframe. Rice yields also have exhibited an overall increase in most of the municipalities, yet with the different pattern of heterogeneity. Municipalities in the middle of Japan have experienced the most negative change in rice yields.

While those areas with yields seem partially associated with temperature distribution in Figure 1, we observe more similar pattern to the distribution of farmers' age as displayed in Figure 3. An averaged farmer in southern Japan is older than in northern Japan, positing the negative association of age and rice yields.

Figure 4 provides additional insights about the nonlinear relationship between age and rice yields. By plotting municipality average rice yields and farmers' age over the period, we observe the inverted U-shaped relationship between age and rice yields. This is consistent with the previous studies (e.g., Tauer 2017). Also, such a relationship is more apparent in the municipalities with the lower level of community engagement regarding common property management of the irrigation system. In other words, more participation of farmers in local community activities seems to offset the age effect on rice yields. Given these observations, we quantify to what degree farmers' age and community engagement play a role in shaping the inverted U-shaped temperature–yield relationship.

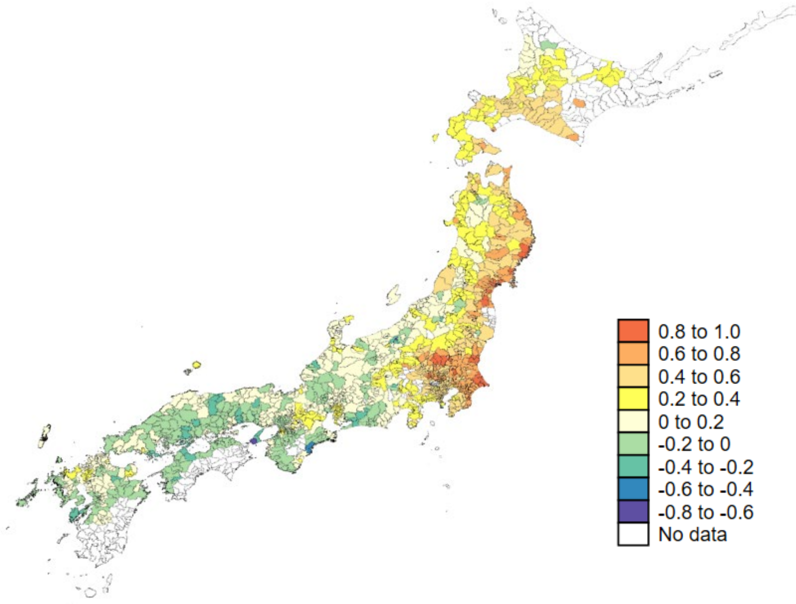

Figure 1: Change in temperatures over 2001–2018 (°C)

Notes: The difference in average temperatures between the 2001–2005 and 2014–2018 periods is calculated for each municipality. Daily mean temperatures are averaged over the rice-growing season (April to October) in each year before computing its average over the respective periods above. Municipalities with no data are not targeted in our study because of no rice production or double cropping.

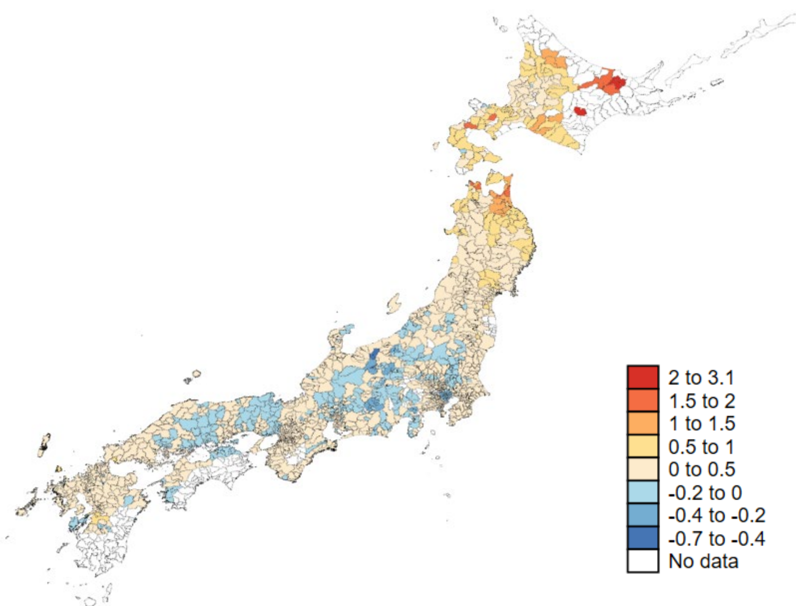

Figure 2: Change in rice yields over 2001–2018 (t/ha)

Notes: The difference in average yields between the 2001–2005 and 2014–2018 periods is calculated for each municipality. Municipalities with no data are not targeted in our study because of no rice production or double cropping.

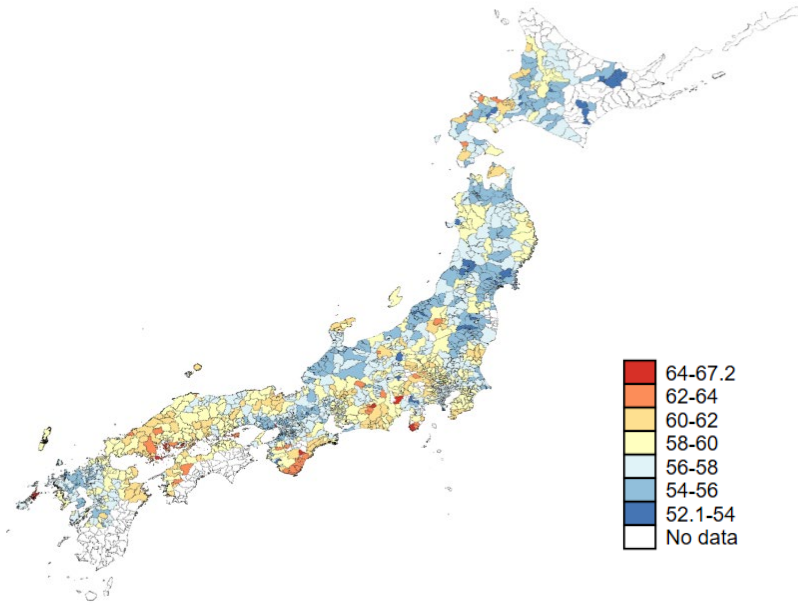

Figure 3: Municipality–average age over 2001–2018 (years old)

Notes: We visualize the farmers' mean age of each municipality averaged over 2001–2018 for each municipality. Municipalities with no data are not targeted in our study because of no rice production or double cropping.

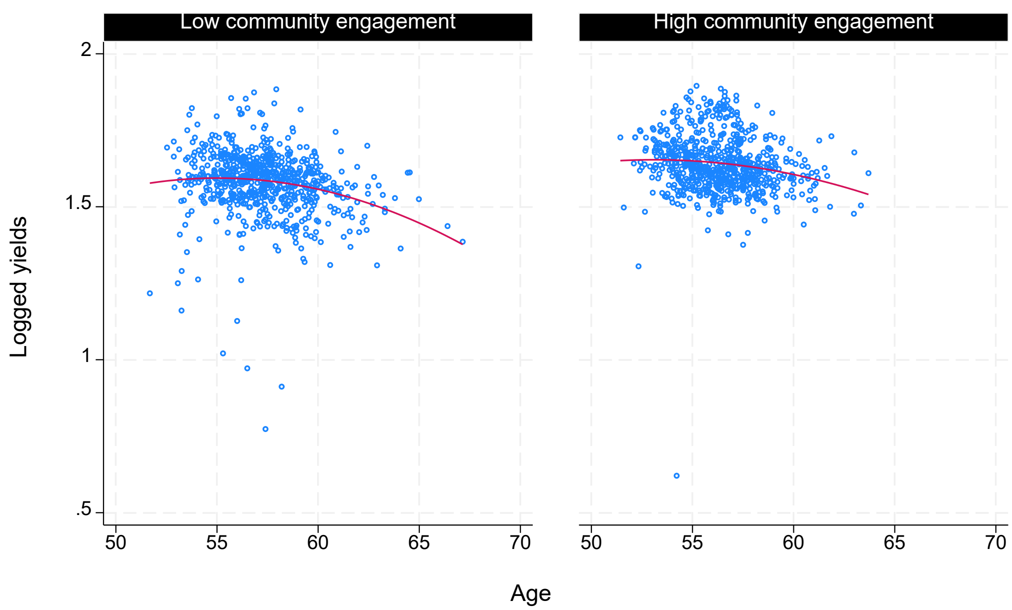

Figure 4: Association of average rice yields and average farmers' age over 2001–2018 in municipalities at the different level of community engagement

Notes: We divide our sample of 1398 municipalities by the 50 percentiles of a community participation rate. The community participation rate is computed based on the number of local farm communities within each municipality which hold periodical meetings regarding common property management of the irrigation system. Each plot represents logged rice yields and farmers' mean age of each municipality averaged over 2001-2018.

III. Methodology and Data

A. Methodology

To estimate how farmers' age influences the temperature–yield relationship, we employ the following empirical model:

$$\ln(Y_{it}) = \Phi(T_{it}, \mathrm{X}_{it}) + \mathbf{Z}_{it}\gamma + \mathrm{C}_i + \lambda_{pt} + \varepsilon_{it}, \qquad (1)$$

where Y_{it} is the rice yield in the municipality *i* in year *t*, Φ represents a flexible function of temperatures T_{it} and farmers' age X_{it}, a vector $\mathbf{Z}_{it}$ includes the other characteristics of farms (average farm size, the share of full-/part-time status and the number of machinery) and the other weather variables (cumulative daily precipitation and global solar radiation over the growing season), C_i represents the municipality fixed effects, λ_{pt} represents the prefecture-by-year fixed effects, and ε_{it} indicates the error term. The municipality fixed effects account for heterogenous place-based attributes such as geography and soils, and the time-varying prefecture fixed effects account for the regional technological change through new crop varieties and other climate-resilient practices introduced by extension services and policy interventions.

For the function $\Phi,$ we adopt a semiparametric form of temperatures to account for nonlinear relationship between temperatures and yields. We construct temperature bins where we count the number of days of the daily mean temperature in certain temperature intervals defined in the next subsection. The nonlinear effect of farmers' age is measured by interacting both average farmers' age and its squared term with the temperature bins. We also include the interaction terms with the other weather variables in $\mathbf{Z}$.

We further explore the extent to which active local community engagement alters the age effect on the temperature–yield relationship. We use a rate of local community participation to separate the sample municipalities into two: high participation group and low participation group, and estimate Equation (1) for each group.

B. Data

The agriculture data used in this study is obtained from the following sources in Ministry of Agriculture, Forestry and Fisheries (MAFF).[6] We collect the annual data of rice-planted area and rice production from 2001 to 2018 at the municipality level from Crop Statistics (Sakumotu Tokei Sakkyou Kome). Based on the rice-planted area and rice production data, we calculate the rice yield in each year for each municipality. Farm characteristic data—farmers' age, farm size, full-/part-time farmers' ratio, and machinery—and local community participation data are obtained from quinquennial Agricultural Censuses in years 2000 to 2015.

Farmers' age is available for all farmers. It can represent age of rice farmers because more than 70 percent of farmers produce rice as a primary crop as seen in Figure A1. To check the potential measurement error, we perform robustness check in the following section by excluding municipalities with a low percentage of rice-farm households. We construct a continuous age variable by interpolating non-census years. We also construct the variable of local community engagement based on a community participation rate, computed from the number of local farm communities within each municipality which hold periodical meetings regarding common property management of the irrigation system.

The weather data applied in this study is acquired from Agro-Meteorological Grid Square Data, NARO.[7] They provide the daily data on temperature, precipitation, and global solar radiation by 1km grid covering entire Japan. To align the grid-level data with municipality-level data, we utilize a list of mesh codes by municipality provided by the Statistics Bureau of Japan, facilitating the integration of these datasets for our analysis. We then construct municipality-level temperature bin variables during the rice growing season from April to October.[8]

We specifically focus on single cropping municipalities.[9] Appendix Figure A2 presents the rice growing status of each municipality in Japan, revealing that single cropping municipalities make up a substantial majority,

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6 See Ministry of Agriculture, Forestry and Fisheries for more detailed information: https://www.maff.go.jp/.

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

8 There exist some differences in the growing season between northern and southern prefectures in Japan. Northern regions tend to have slightly later planting and harvesting dates compared to southern areas, although these differences are not substantial. These variations remain within the range from April to October. Data on the rice growing season is available upon request.

9 In Japan, 42 out of 47 prefectures conduct single cropping and the rest of 5 prefectures (Tokushima, Kochi, Miyazaki, Kagoshima, and Okinawa) perform double cropping for paddy rice. Those 5 prefectures are excluded in this research.

accounting for about 90 percent of all rice producing municipalities. The remaining 9.8 percent engage in double cropping. Among the single cropping municipalities, we keep 92 percent of them that continue rice production over the sample period. Only 5.9 percent of municipalities never produced rice, and about 1 percent discontinued rice cultivation. This leaves 1398 sample municipalities.

Table 1 presents the summary statistics of the main variables in our study. The average rice yields among the sample municipalities from 2001 to 2018 are 5.1 tonnage per hectare (t/ha). During the rice growing season (214 days), the number of days experiencing daily mean temperature below 15°C totals 56.4 days and above 27°C amounts to 14.6 days on average. Figure 5 illustrates the distribution of daily mean temperature over six temperature bins (<15°C, 15°C –18°C, 18°C –21°C, 21°C –24°C, 24°C –27°C, >27°C). The average sum of daily precipitation and daily global solar radiation during the growing season are 1216.8 mm and 3314.8 MJ/m2, respectively. The average age of farmers is 58.0 years old with spatial heterogeneities among municipalities as shown above in Figure 3.

Table 1—Summary statistics (*N* = 24,558)

	Mean	SD	Min	Max
Rice yield (t/ha)	5.1	0.6	0.2	7.0
<15°C (days)	56.4	33.9	3	192
15°C–18°C (days)	36.3	8.1	11	69
18°C–21°C (days)	41.0	8.8	1	74
21°C–24°C (days)	36.7	12.5	0	79
24°C–27°C (days)	29.0	17.4	0	79
>27°C (days)	14.6	17.0	0	70
Precipitation (mm)	1216.8	396.8	373.7	4216.6
Global Solar Radiation (MJ/m^2)	3314.8	229.2	2505.9	4785.8
Age (years old)	58.0	2.9	48.1	72.4

Notes: Slightly unbalanced panel data consists of 1398 municipalities in 2001-2018. The weather variables are constructed based on the rice growing season in April to October.

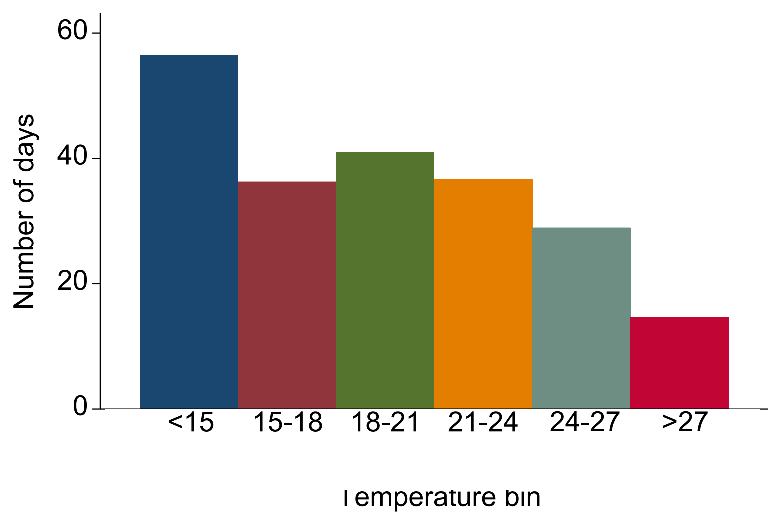

Figure 5: Distribution of daily mean temperature during the crop growing season over 2001–2018

Notes: The figure represents the average number of days per year during the rice growing season in each temperature bin (<15, 15–18, 18–21, 21–24, 24–27, >27°C). These are summed up in 214 days.

IV. Empirical Results

A. Yield–Temperature Response Function

Before presenting our regression results of the age effect on the temperature–yield relationship, we first quantify the temperature–yield relationship. The estimation results are presented in Table 2. Column 1 presents two-way fixed effect estimation results, Column 2 introduces the prefecture-specific year fixed effects, and Column 3 includes additional control variables as delineated in the data section. We choose the 21°C–24°C bin as reference according to the agronomy literature.[10]

Overall, we find the significantly negative response of rice yields to both extremely cold and warm temperature bins. Our preferred specification in Column (3) shows that exposure to an additional day below 15°C decreases rice yields by 0.20 percent, and an extra day above 27°C reduces rice yields by 0.08 percent.[11] Precipitation appears to have no significant impact on rice yields because the irrigation system is widely practiced for paddy rice production

[10] 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°C to 24°C. The maximum grain weight was observed at 24°C in Wakamatsu et al. (2007) and 19°C to 25°C in Yoshida and Hara (1977).

[11] We also performed robustness check at different clustering and with different temperature functions. Results are robust among them as provided in Appendix Figure A3.

in Japan. Solar radiation shows weak evidence of its inverted U-shaped relationship with rice yields.

Figure 6 displays the yield–temperature response function in Column (3) with the 95 percent confidence intervals. The results indicate that rice productivity in Japan is particularly susceptible to cold temperatures, consistent with the finding of Kawasaki and Uchida (2016) at the prefecture-level analysis.

Table 2—Results of the nonlinear temperature effects on rice yields

	(1)	(2)	(3)
<15°C	-0.0038	-0.0021	-0.0020
	(0.0012)	(0.0008)	(0.0008)
15°C–18°C	-0.0023	-0.0003	-0.0002
	(0.0007)	(0.0003)	(0.0003)
18°C–21°C	-0.0005	0.0001	0.0001
	(0.0003)	(0.0002)	(0.0002)
24°C–27°C	-0.0001	-0.0004	-0.0004
	(0.0003)	(0.0002)	(0.0002)
>27°C	-0.0008	-0.0008	-0.0008
	(0.0004)	(0.0003)	(0.0003)
Precipitation (1000mm)	0.0567	0.0285	0.0275
	(0.0242)	(0.0433)	(0.0422)
Precipitation squared	-0.0253	-0.0066	-0.0063
	(0.0094)	(0.0112)	(0.0110)
Solar radiation (100 MJ/m^2)	0.0450	0.0767	0.0758
	(0.0351)	(0.0433)	(0.0424)
Solar radiation squared	-0.0006	-0.0011	-0.0010
	(0.0005)	(0.0006)	(0.0006)
Municipality fixed effects	YES	YES	YES
Year fixed effects	National	Prefecture	Prefecture
Control variables	NO	NO	YES
Observation	24,558	24,558	24,558
Adjusted R^2	0.768	0.768	0.768

Notes: Our sample consists of single cropping municipalities which continuously produce rice in 2001–2018. Standard errors clustered at the prefecture level are reported in parentheses. Regressions are weighted by the average rice planted area for the years 2001–2018. ***, **, and * denote 1 percent, 5 percent, and 10 percent significant level, respectively.

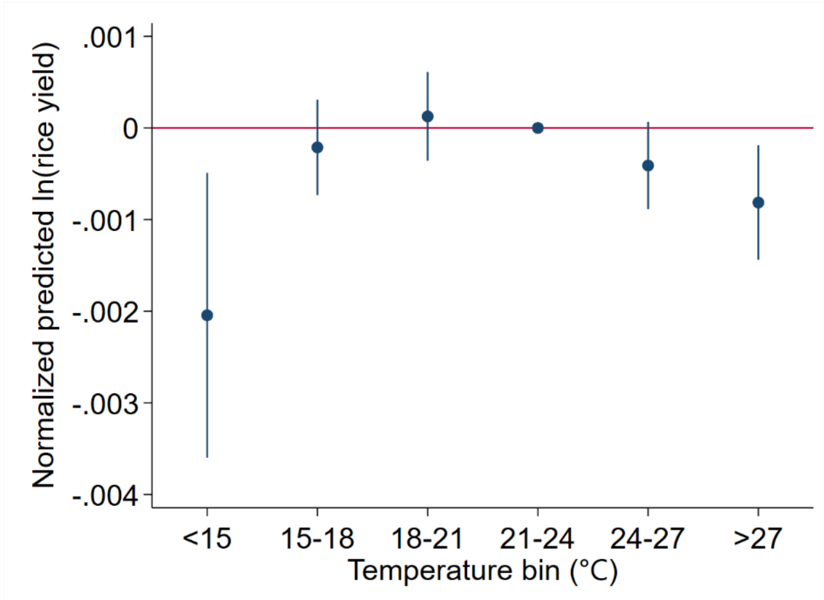

Figure 6: Relationship between temperature and rice yields

Notes: We plot point estimates in Column (3) of Table 2 where the vertical lines represent 95 percent confidence intervals.

B. Farmer Age and the Yield–Temperature Relationship

Results in Table 3 indicate that farmers' age has the significant nonlinear influence on the yield response function. The curvature of the yield response function is amplified by increasing/decreasing farmers' age from the threshold age. The threshold age, which minimizes the negative effect of extreme temperatures below 15°C and above 27°C, is found to be 60.2 and 59.8 years old, respectively. Figure 7 illustrates the yield response function for farmer's age evaluated at 50, 60 and 70 years old.[12] Farmers aged around 60 show the highest resilience to extreme temperatures, exhibiting no statistically significant loss from hot temperatures. Below and above the threshold age (those aged 50 and 70 in the figure, for instance), farmers become significantly vulnerable to extreme temperatures.

To more closely illustrate the role of age in moderating the extreme temperature effects on yields, we plot the marginal age effect on the yield response to the coldest (<15°C) and hottest (>27°C) temperature bins evaluated at each of the age distribution in Figure 8. The horizontal axis of Figure 8 represents farmers' age, and the vertical

[12] We use an average age of 50 and 70 as approximation of minimum (48.1) and maximum (72.4) values in our sample municipalities, respectively, for simple illustration.

axis indicates the estimated yield impact associated with the exposure to an additional day in the coldest (<15°C) and hottest (>27°C) temperature bins relative to the reference bin of 21°C–24°C. An inverted U-shaped relationship appears between age and the yield response to the extreme temperatures, highlighting the importance of farmer's age as climate adaptation capability.

We see from Figure 8 that, below the threshold age of about 60, farmers become more capable of adapting to extreme temperatures with increasing age. Young farmers can accumulate valuable experiences and knowledge through learning-by-doing from daily production activities. Above the threshold age, farmers' adaptation capability diminishes. This is likely because the positive aging effect of cumulative experiences and knowledge is overwhelmed by the negative aging effect. Generally, as age increases, physical and cognitive abilities decline, making it difficult to adapt to new environmental changes (Barnes et al. 2019; Shang et al. 2021). Also, old farmers are less aware of climate change (Tamura et al. 2021). Moreover, elderly farmers approaching retirement have little incentive to invest in costly new technologies. Consequently, they become less resilient to extreme temperatures.

We perform robustness check with the alternative definition of farmer's age. By using the share of farmers in each age category as an explanatory variable instead of municipality-level average age, we obtain qualitatively same relationship between age and the crop response function (See Appendix Figure A5). We also investigate the potential endogeneity of age because temperature-driven yield loss could cause the exit of inefficient old farmers from production and promotes the entry of efficient young farmers, so that the distribution of both age and yields changes simultaneously. We find no significant relationship between extreme temperatures in past years and the present age (See Appendix Table A1).

Table 3—Aging effect on the rice yield response function to temperatures

	Single term of temperature bins	Cross term with age	Cross term with age squared
<15°C	-0.1780	0.0059	-0.000049
	(0.0690)	(0.0023)	(0.000019)
15°C–18°C	-0.0539	0.0018	-0.000016
	(0.0385)	(0.0013)	(0.000011)
18°C–21°C	-0.0594	0.0021	-0.000018
	(0.0459)	(0.0015)	(0.000013)
24°C–27°C	-0.1775	0.0060	-0.000050
	(0.0845)	(0.0029)	(0.000024)
>27°C	-0.2172	0.0073	-0.000061
	(0.0875)	(0.0030)	(0.000025)

Notes: We provide the coefficient estimates of temperature bins and their interaction terms with age and age squared, defined in Section III.A. We use the same sample with the same set of fixed effects and control variables as in column (3) in Table 2. Adjusted R^2 is 0.771. Our sample consists of single cropping municipalities which continuously produce rice in 2001-2018. Standard errors clustered at the prefecture level are reported in parentheses. Regressions are weighted by the 2001–2018 average rice planted area. ***, **, and * denote 1 percent, 5 percent, and 10 percent significant level, respectively.

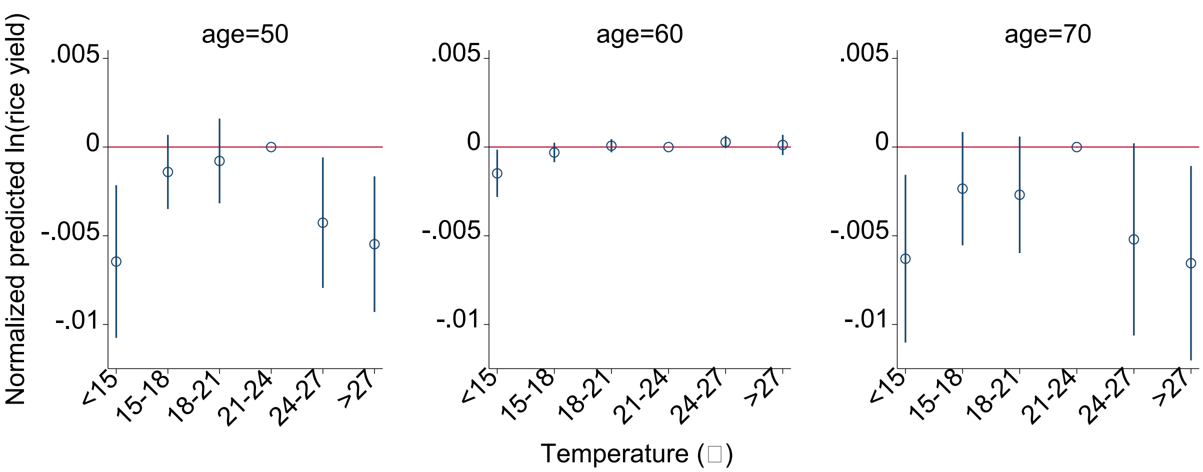

Figure 7: Age effect on the yield response function

Notes: We plot the linear combination of point estimates of respective temperature bins in Table 3 with the vertical line of their 95 percent confidence intervals, when age is evaluated at 50, 60, and 70.

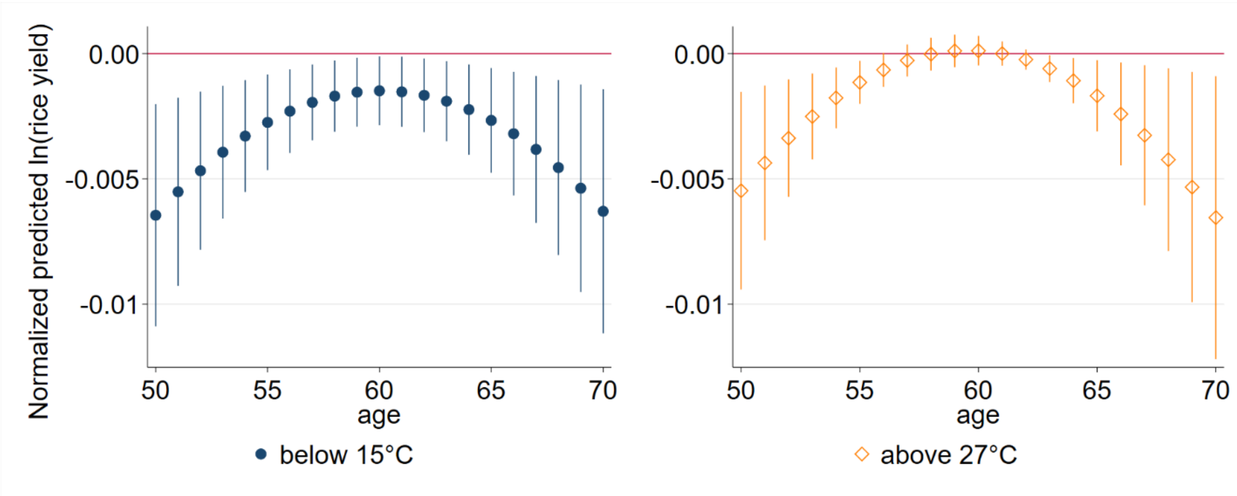

Figure 8: Marginal age effects on the yield response function to <15°C and >27°C bins

Notes: We plot the estimated marginal age effects of an additional day in the <15°C and >27°C temperature bins on rice yields relative to the 21°C–24°C bin as the reference. Vertical lines represent 95 percent confidence intervals. Estimates are derived from Table 3.

C. Effects of Community Engagement and Aging on the Temperature–Yield Relationship

Next, we examine whether engagement of farmers in local community activities moderates the negative age effect on the temperature–yield relationship. We split our sample municipalities by the lower/higher share of involvement in local community activities, and analyze the age effect for each subsample group.

Figure 9 illustrates how the degree of community engagement influences the age and temperature–yield relationship under the three age scenarios.[13] The negative age effect of a farmer is minimal at age about 60 who is most resilient to extreme temperatures, regardless of local community engagement. In contrast, the negative age effect for the extreme temperatures is magnified for farmers at ages 50 and 70, particularly at the lower level of community engagement. It is also noted that the negative age effect for the extreme temperatures has much larger standard errors in the communities with lower engagement level than those with higher engagement level. This

[13] Point estimates are provided in Appendix Table A2. The threshold age, which minimizes the negative temperature impact, consistently falls in the late 50s. To check the heterogeneous effect of temperatures on yields, we estimate the temperature response function for each subsample and test the difference in point estimates by using the Bonferroni adjusted p-values. We cannot reject the null hypothesis. Results are available upon request.

indicates farmer's varying adaptation capabilities across malfunctioning communities.

Figure 10 depicts the same inverted U-shaped relationship between age and the yield response to the extreme temperatures as in Figure 8, except that two different curves illustrate how community engagement level shapes the curvature of the marginal age effect on the temperature–yield relationship. A more pronounced inverted U-shaped relationship appears in municipalities with low community engagement, where yield losses are steeper among both younger and older farmers. In contrast, in municipalities with high engagement, the curvature is flatter, indicating that community networks help buffer the age-related vulnerability to extreme temperatures. The results suggest that active community participation can form social bonds to reinforce young/elderly farmers' adaptive capability to extreme temperatures. Some study shows that community engagement allows farmers to gain access to innovative practices, leading to increased yields (Abdul-Rahaman and Abdulai 2018). Our results also imply that mutual assistance among farmers in the community by information sharing and co-management of common facilities enable vulnerable community members to acquire know-how to accommodate with the negative production shocks.

The results are robust when we use the share of farmers in each of the three age categories instead of municipality-level average age (Appendix Figures A6). We also obtain similar results with different specifications of community engagement—by interacting a continuous community engagement variable with temperature bins and age variables; and using time-varying percentiles to define increases/ decreases in community engagement between 2000 and 2015.[14]

[14] Similar results were also obtained when computing a community participation rate for the other purposes of meeting such as farm production and other common facilities. Results of parameter estimates are available upon request.

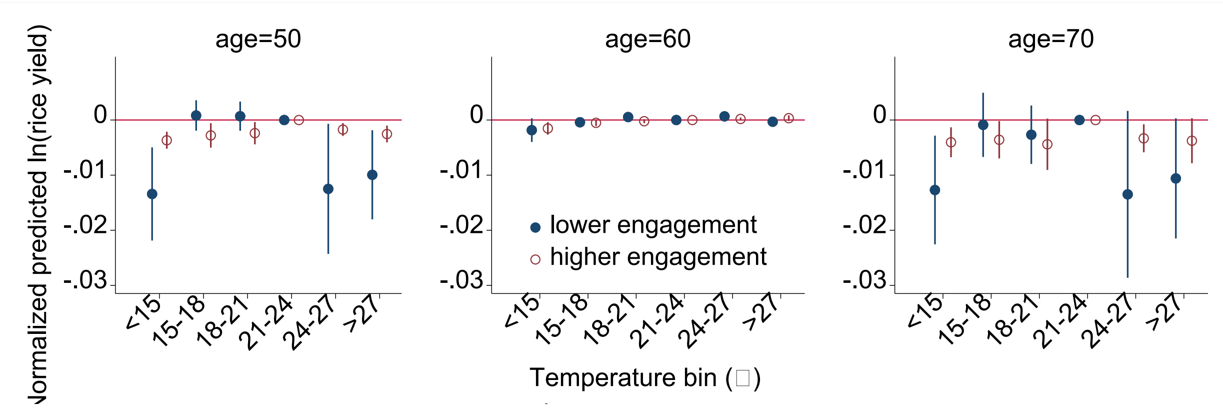

Figure 9: Relationship between age and temperature–rice yields for municipalities with the lower vs higher share of local community engagement

Notes: Same plots as in Figure 7, except that we estimate a set of parameters for the sample with the lower and higher levels of community engagement.

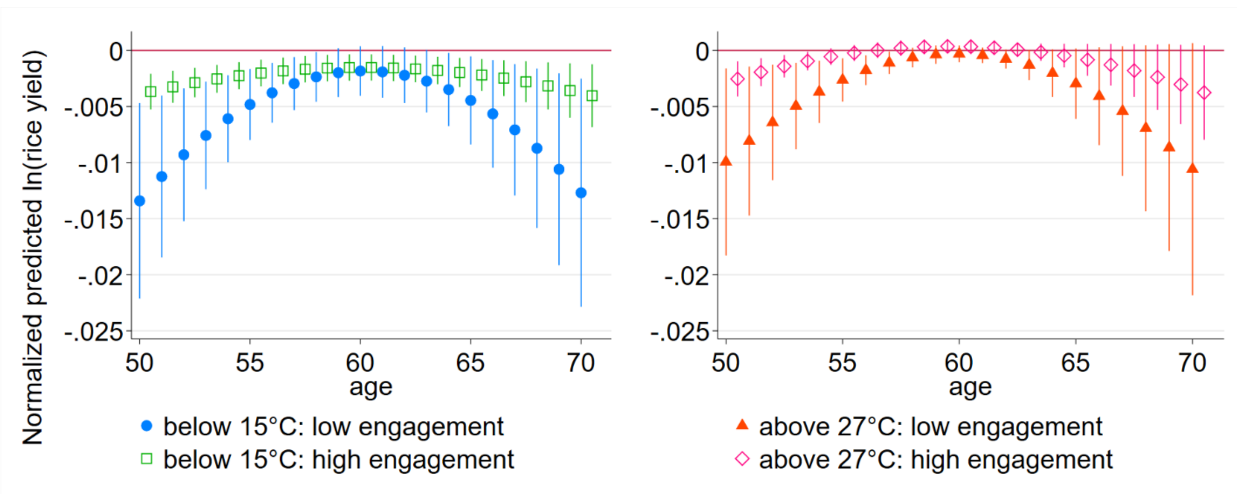

Figure 10: Marginal age effects on the yield response function to <15°C and >27°C bins: By municipalities with the lower vs higher share of local community engagement

Notes: Same plots as in Figure 8, except that we use a set of parameter estimates for each of the subsamples with the lower and higher levels of community engagement.

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V. Simulation of the Aging and Community Effects

In the previous section, we showed the quadratic age effect on the crop response function to extreme temperatures, and discussed how the farmers' cooperative behavior in local communities can serve as a social capital to compensate the negative age effect on too-young and too-old farmers. Here, we aim to demonstrate the extent to which such community involvement can offset the negative age effect under future global warming scenarios. To do so, we compute the percentage change in rice yields from the current status quo to the following seven scenarios which shift temperatures and farmers' age such that:[15]

(i) An increase in temperatures by 1°C under current age;

(ii) An increase in temperatures by 2°C under current age;

(iii) An increase in temperatures by 4°C under current age;

(iv) An increase in farmers' age by 5 years under current temperatures;

(v) An increase in temperatures by 1°C and an increase in farmers' age by 5 years;

(vi) An increase in temperatures by 2°C and an increase in farmers' age by 5 years; and

(vii) An increase in temperatures by 4°C and an increase in farmers' age by 5 years.

Scenarios (i) to (iii) compute the effects of increasing temperatures alone, while Scenario (iv) assesses the sole effect of aging. Scenarios (v) to (vii) calculate the combined effects of an increase in temperatures and aging. We follow the IPCC RCP scenarios to decide a range of temperature increase in our scenarios. Also, we assume a 5-year increase in average farmers' age in the next decades based on the trend of overall farm aging according to the Agricultural Censuses.[16] We simulate these seven scenarios for municipalities with the currently lower status of local community engagement, so that we also evaluate the community effect as if their engagement level were shifted to higher.

Figure 11 displays the average percentage change in rice yields for the seven scenarios.[17] Because the

[15] We compute predicted values by increasing temperatures and age, while keeping all the other weather and farm variables constant.
[16] Simulation with more than five years of aging is qualitatively same, rather inflating the negative effects.
[17] Exact numbers are provided in Appendix Table A3.

temperature increase will lead to differential effects of colder and warmer temperatures than the reference temperature bin (21–24°C), we analyze the seven scenarios for colder temperature bins (<15°C, 15–18°C, 18–21°C) and warmer temperature bins (24–27°C, >27°C) separately. Colors in blue and red represent simulation results for the colder and warmer bins, respectively. We observe in Scenarios (i)-(iii) that a rise in colder temperatures (less than 21°C) improves rice yields, while a rise in warmer temperatures (more than 24°C) decreases rice yields. Rice yields increase by about 3-10 percent when the colder temperatures rise by 1-4°C depending on the warming scenarios, while yields decrease by about 1-5 percent due to an increase of 1-4°C in the warmer temperatures. These findings are consistent with Kawasaki and Uchida (2016) suggesting that global warming can benefit Japan's rice yields overall, but it can also generate inequality among different climate regions.

However, this conclusion fails to account for the farmers' adaptation capability affected by aging. In Scenario (iv) where we predict with a 5-year increase in average farmer age, yields significantly decrease for both the colder and warmer temperatures by about 7% and 5%, respectively. This indicates that, in the aging farm community, the negative aging effect of elderly farmers outweighs the positive aging effect of young farmers. This net negative effect of aging is partly offset by the benefit from temperature increases for the colder temperatures under Scenarios (v)-(viii). In contrast, the negative aging effect amplifies the negative effect of temperature rise for the warmer temperatures. These results imply that rice yields are more affected by aging than temperature rise, and that combination of them makes rice production further vulnerable in warm-climate regions. It is also noted that this vulnerability is considerably higher when we focus only on the municipalities with older farmers as seen in Appendix Figure A7.

Notwithstanding, the negative aging and warming effects can be offset by social capital formation. Figure 12 presents the effect of switching the status of local community engagement from low to high on the temperature and age effects in Figure 11. Solid blue and red line plots in Panels A and B are the same as plots in Figure 11 for the colder and warmer temperatures, respectively, for municipalities with the currently lower status of local community engagement. Dotted line plots show the percentage change in rice yields under the seven scenarios for the same municipalities that behave as if their status become higher. Marked improvement in yields is observed for warmer temperatures under Scenarios (iv)-(vii) in Panel B of Figure 12, where the higher level of community engagement negates by more than half of the negative combination effect of aging and warming. For the colder temperature bins of <15°C, 15–18°C, 18–21°C in Panel A, the relative change of rice yields is higher when the community engagement level is low simply because an increase in temperatures merits more for such a community.[18]

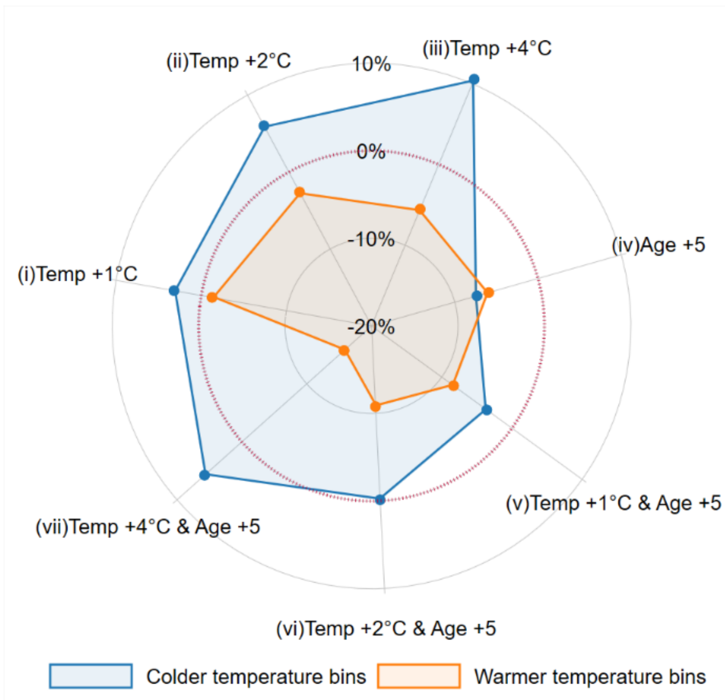
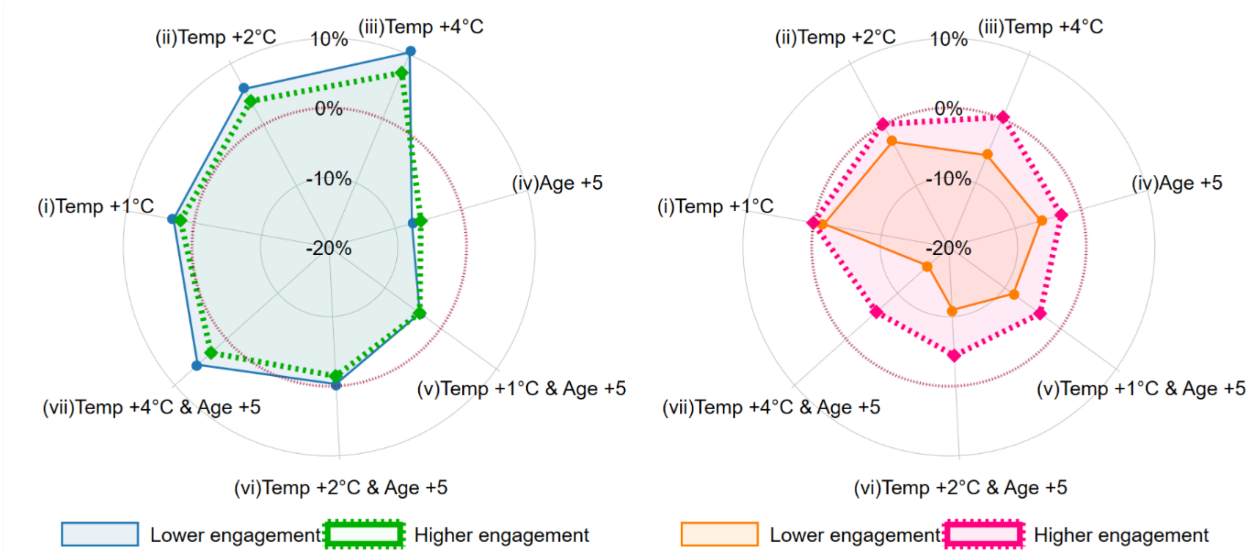


Figure 11: Percentage change in rice yields under future temperature and age scenarios for municipalities at the lower level of local community engagement

[18] The difference between lower and higher engagement appears small for the cold temperature bins because we get the reverse relationship in the estimated coefficient of the temperature bin of <15°C and that of 15–18°C and 18–21°C as seen in Figure 9.



Panel A. Colder temperature bins

Panel B. Warmer temperature bins

Figure 12: Percentage change in rice yields under future temperature and age scenarios at the different level of community engagement

VI. Conclusion

This study quantified the evidence of famer's adaptation capability to climate change. We found that at an optimal farmer's age, crop production is reasonably adapted to extreme cold and warm temperatures. In case of Japanese rice farmers, the gradient of the crop yield response function is effectively flat in municipalities with an average age of farmers around 60 years old. In contrast, municipalities with older or younger farmers show limitations to adapt, experiencing significant yield losses from extreme temperatures. Our simulation results indicate that, in the aging farm community, the progress of further aging and global warming will deteriorate rice yields at a nontrivial rate. However, such losses can be mitigated with more active community engagement by farm community members, which can augment the adaptive capability of retiring and beginning farmers in the face of the extreme temperatures.

While structural transformation by farm merger and/or succession may alternate solution to the aging problem in the long run, policymakers should prioritize aging farm population in designing climate change adaptation strategies at present. By considering the varying capabilities of elderly farmers to adapt to climate change, policies can be more targeted, ensuring that resources are allocated effectively and fostering resilience within the agricultural sector. A key solution for effective adaptation hinges upon reinforcing networks and relationships among farm community members through active engagement in the community, which can facilitate knowledge sharing, resource pooling, and collective action, thereby enabling farmers to increase their resilience to the challenges posed by aging and warming. This may be tagged with extension services by the public sector which play a role not only in fostering and incentivizing the adoption of climate-resilient practices and technologies but also accelerating communication among farmers for active community engagement.

Aging of the farming population also occurs in other regions such as the United States and Europe. According to the US Census of Agriculture, the average age of US farmers is 58.1 in 2022, up 7.8 years from 1978. In the latest statistics in the EU only 11 percent of farmers were under the age of 40.[19] Similar to Japan, further aging in the farm society could reduce crop yields, and this issue may be more pronounced for crops that are sensitive to heat rather than cold. For example, numerous studies have shown that corn and soybeans in the United States are highly sensitive to extreme heat (e.g., Schlenker and Roberts, 2009; Burke and Emerick, 2016). Understanding and addressing the adaptation capability of farmers is an urgent agenda in these countries, too.

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[19] 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 for more detailed information: https://ec.europa.eu/eurostat/databrowser/view/ef_m_farmang/default/table?lang=en.

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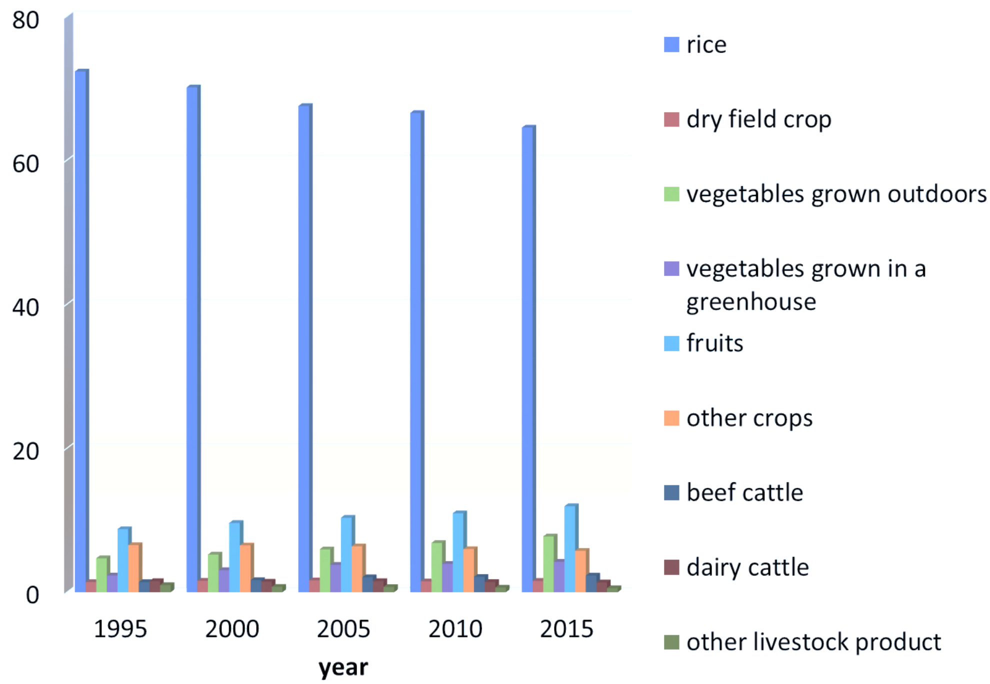
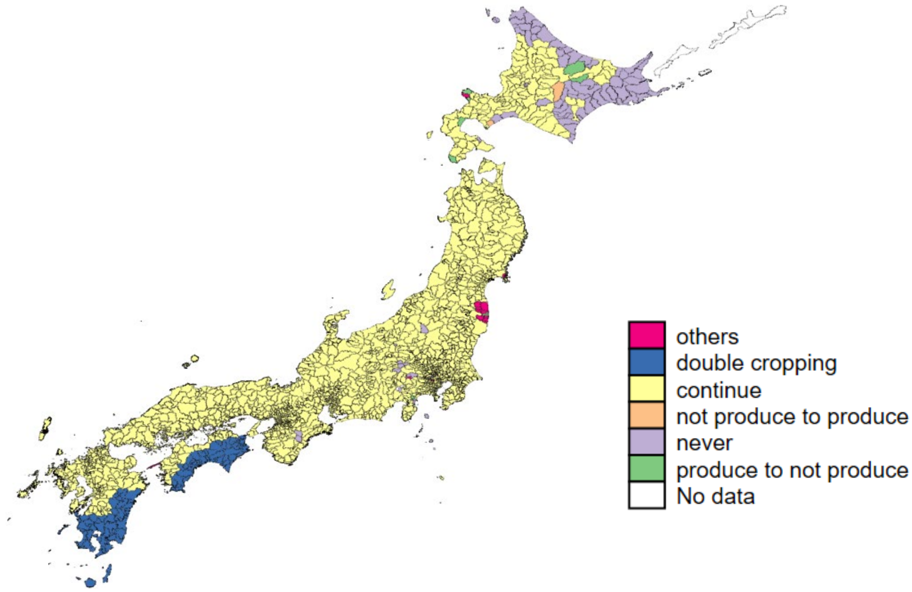
APPENDIX

Figure A1: Percentage of farm households by crop and livestock (%) in Japan



Notes: The number of each crop and livestock farm household data is attained from MAFF quinquennial agricultural censuses, 1995–2015. Only single enterprise farm data is used (farm that sells 80 percent or more of the value of its agricultural product sales in the primary crop).

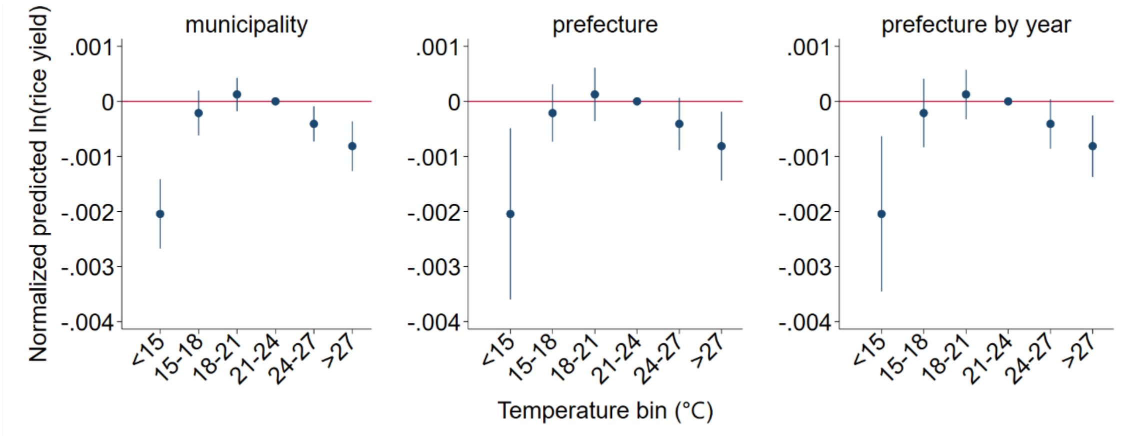
Figure A2. Rice growing status of each municipality in Japan over 2001–2018



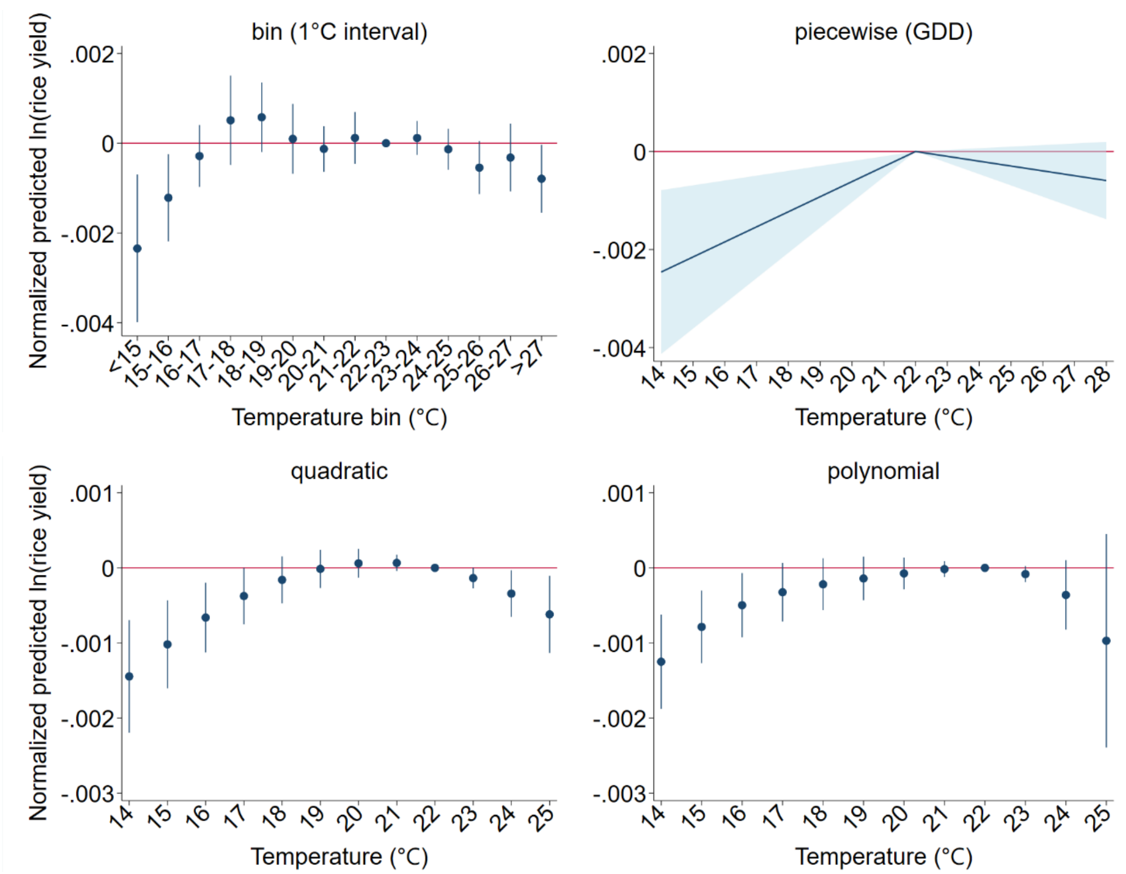
Notes: Purple indicates the municipalities which never produce rice. Yellow presents the municipalities which continuously grow rice. Green (or Orange) color shows the municipalities which originally produced (or did not produce) rice but eventually quit (or start) growing rice. Blue gives the double-cropping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

Figure A3. Robustness check

Panel A. Cluster standard error at the different level

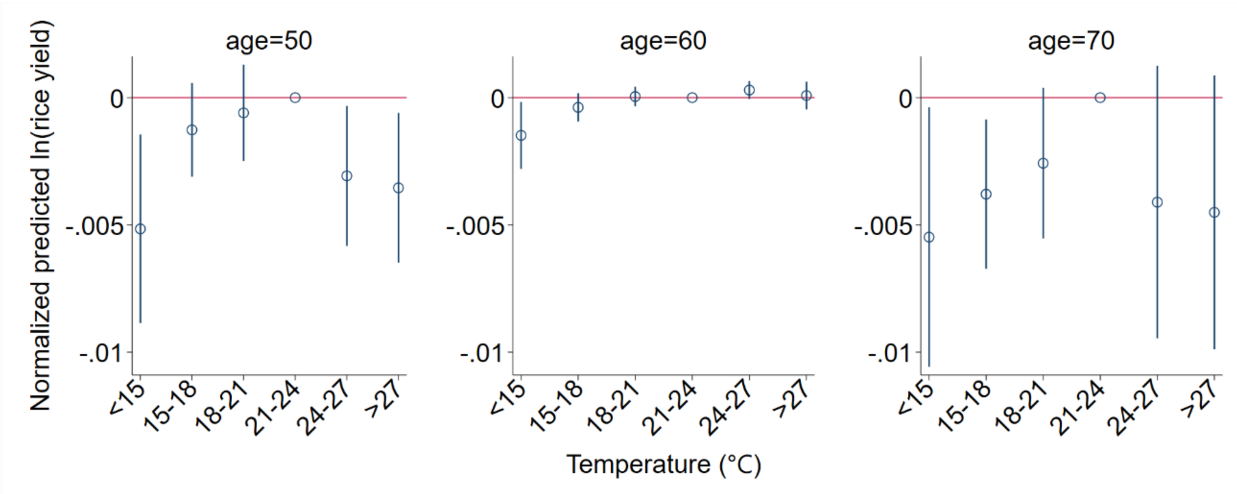


Panel B. Model selections



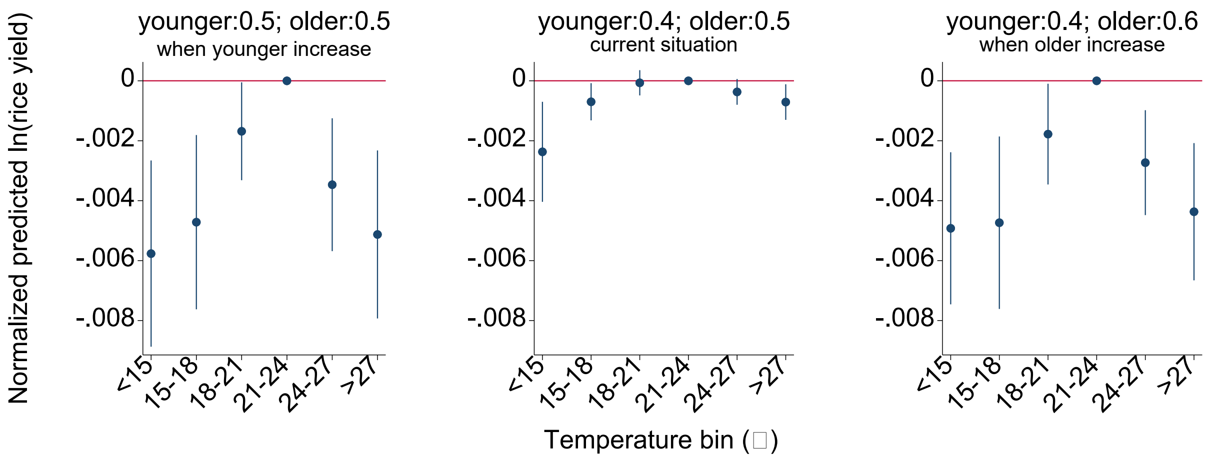
Notes: In Panel A, we check with different clustered standard errors for estimation results in Column (3) in Table 2. In Panel B, we check four additional specifications of temperature variables. The first model uses the 1°C bins. The piecewise model computes the growing degree days by using the mean daily temperature for the growing season of each year. For the quadratic specification, we use the linear and quadratic terms of the mean daily temperature in the model. The polynomial specification extends the quadratic model to include terms up to the fifth order.

Figure A4. Robustness check for the relationship between age and temperature–rice yields: Exclude municipalities with the share of rice-farm households less than 25 percent



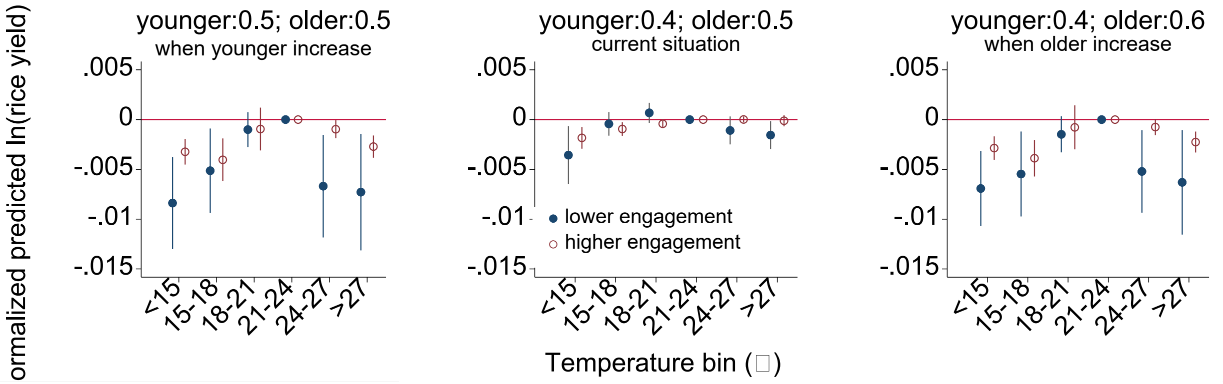
Note: Same specification is used for estimation as in Figure 6. The number of observations is 22,127 (1,247 municipalities).

Figure A5. Robustness check for the relationship between the share of farmers in each age category and temperature–rice yields: Three age categories of 15–54 years old (younger), 55–59 years old (base category), and above 60 years old (older)



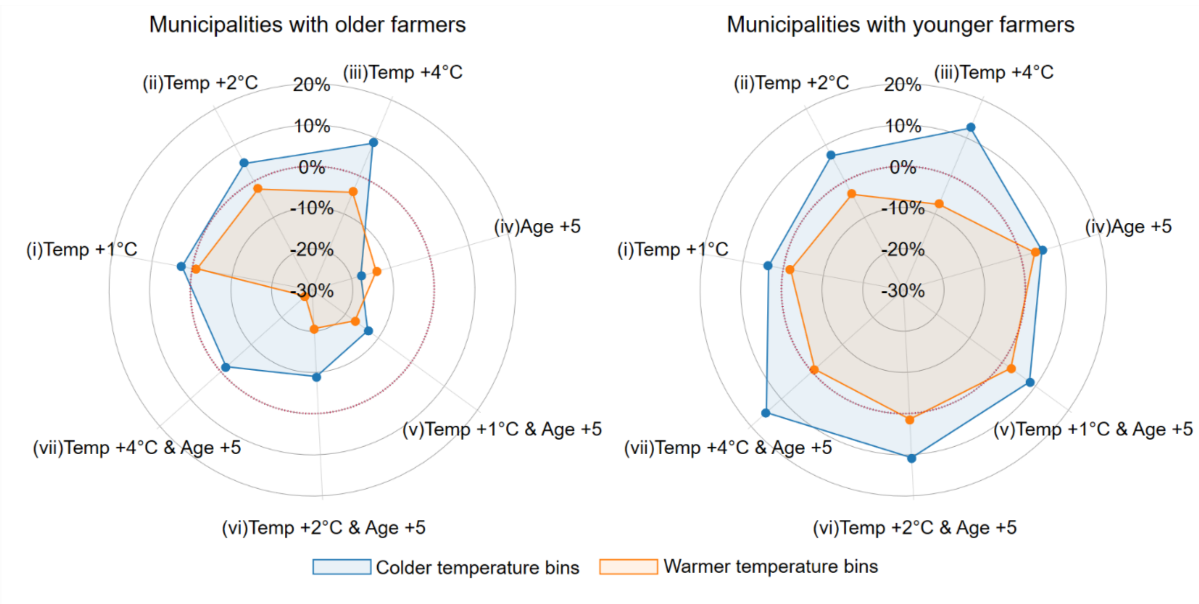
Note: The share of each of the three age categories are used instead of the average age variable. Estimates of the share variables are then used to compute the yield response function to temperatures for the three cases similar to those in Figure 7: More younger farmers (50% of total farm households) on the left; intermediate; and more older farmers (60%) on the right. The number of observations is 24,558.

Figure A6. Relationship between the share of farmers in the age categories and temperature–rice yields: Municipalities lower vs higher share of local community engagement—agricultural drainage channels



Note: See notes in Figure A5.

Figure A7. Percentage change in rice yields under future temperature and age scenarios for municipalities at the lower level of local community engagement: By the age of farmers



Note: We present the simulation results in Figure 11 for two subgroups which are divided by the 50 percentiles of an average age of farmers in sample municipalities. An average age of farmers in the subsample with older farmers is 60 years, while the younger subsample has an average age is 56 years.

Table A1. Endogeneity of age: past 3-year vs past 5-year moving averages for weather variables as explanatory variables

Outcome: Age	(1)	(2)
	Past 3-year	Past 5-year
<15°C	-0.0037	0.0044
	(0.0109)	(0.0158)
15°C–18°C	-0.0025	0.0052
	(0.0082)	(0.0145)
18°C–21°C	-0.0081	-0.0106
	(0.0061)	(0.0112)
24°C–27°C	0.0098	0.0135
	(0.0075)	(0.0108)
>27°C	0.0176	0.0196
	(0.0123)	(0.0159)
Municipality fixed effects	YES	YES
Year fixed effects	Prefecture	Prefecture
Observation	3,959	3,951
Adjusted R^2	0.9337	0.9345

Notes: ***, **, and * denote 1 percent, 5 percent, and 10 percent significant level, respectively. Precipitation and global solar radiation in the past years are included in regression. Only the years 2001, 2006, 2011, and 2016 are used for estimation. Standard errors clustered at the prefecture level are reported in parentheses.

Table A2. The age effect on the rice yield response function to temperatures: Municipalities of lower vs higher community engagement

	Single term	Cross term with age	Cross term with age squared
Low engagement			
<15°C	-0.4077	0.0135	-0.000112
	(0.1487)	(0.0050)	(0.000042)
15–18°C	0.0183	-0.0005	0.000004
	(0.0599)	(0.0021)	(0.000018)
18–21°C	-0.0443	0.0017	-0.000015
	(0.0567)	(0.0020)	(0.000017)
24–27°C	-0.4879	0.0163	-0.000137
	(0.2471)	(0.0083)	(0.000070)
>27°C	-0.3569	0.0119	-0.000100
	(0.1705)	(0.0058)	(0.000049)
Observation: 12,310			
Adjusted R^2: 0.728			
High engagement (N = 12,248)			
<15°C	-0.0845	0.0028	-0.000023
	(0.0298)	(0.0010)	(0.000009)
15–18°C	-0.0944	0.0032	-0.000027
	(0.0436)	(0.0015)	(0.000013)
18–21°C	-0.1084	0.0037	-0.000031
	(0.0552)	(0.0019)	(0.000016)
24–27°C	-0.0928	0.0032	-0.000027
	(0.0311)	(0.0011)	(0.000009)
>27°C	-0.1215	0.0041	-0.000035
	(0.0456)	(0.0016)	(0.000014)
Observation: 12,248			
Adjusted R^2: 0.841			

Notes: Estimation results from Equation (1) with the two-split sample by the level of local community engagement. We use the same set of fixed effects and control variables as in column (3) in Table 2. Our sample consists of single cropping municipalities which continuously produce rice in 2001–2018. Standard errors clustered at the prefecture level are reported in parentheses. Regressions are weighted by the 2001–2018 average rice planted area. ***, **, and * denote 1 percent, 5 percent, and 10 percent significant level, respectively.

Table A3. Difference in the percentage change in rice yields under various temperature and age scenarios

Scenarios	Colder bins: (1) Lower engagement	Colder bins: (2) Higher engagement	Warmer bins: (3) Lower engagement	Warmer bins: (4) Higher engagement
(i) Temp +1C	3.2%	2.0%	-1.3%	0.1%
(ii) Temp +2C	6.0%	3.9%	-2.6%	0.1%
(iii) Temp +4C	10.6%	7.2%	-5.5%	0.3%
(iv) Age +5	-7.3%	-6.1%	-5.9%	-3.0%
(v) Temp +1C & Age +5	-3.6%	-3.8%	-8.3%	-3.7%
(vi) Temp +2C & Age +5	-0.1%	-1.4%	-10.8%	-4.4%
(vii) Temp +4C & Age +5	5.8%	3.0%	-15.8%	-5.9%

Notes: Columns (1) and (3) represent squared plots in blue and red in Figure 11, respectively. They are also plotted in Figure 12 as a baseline. Columns (2) and (4) represent diamond plots with dotted lines in green and pink in Figure 11, respectively.