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The impact of climate change on the labor allocation: Empirical evidence from China[☆]

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ABSTRACT

Climate change may significantly affect the labor market by generating disproportionate damage to marginal returns to labor across sectors. However, this potentially important channel through which climate change may affect social welfare has not received the attention it deserves. We provide the first estimate of the long-term effects of climate change on the labor market based on the hedonic approach, which accounts for individual long-term adjustments to climate change. Using a panel of field survey data from 8076 working age residents in 279 rural communities in China, we find that a 1 °C increase from current mean temperature will reduce an average rural resident's time allocated to farm work by 7.0%, increase the time allocated to off-farm work by 7.8%, and reduce the time allocated to leisure by 0.8%. We also find differential responses to climate change across gender: higher temperatures mainly shift males' time from leisure to off-farm work, but mainly shift females' time from farm work to off-farm work.

1. Introduction

Understanding the socio-economic consequences of climate change is critical to the design of optimal climate policies (Dell et al., 2012; IPCC, 2014). A growing body of literature has identified substantial and far-reaching impacts of climate change on agriculture (Mendelsohn et al., 1994), economic growth (Burke et al., 2015b), civil conflict (Burke et al., 2015a), human health (Deschenes, 2014), human capital (Graff Zivin et al., 2018), and labor productivity (Zhang et al., 2018).[1]

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[1] See Dell et al. (2014) for a thorough review of empirical studies on the impact of climate change on socio-economic outcomes.

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The current study explores the potential impact of climate change on the labor market.[2] Climate change is more likely to damage climate-exposed sectors than sectors less vulnerable to high temperatures (Mendelsohn, 2008; Burke et al., 2015b; Dellink et al., 2017). The disproportionate damage created by climate change generates a gap in marginal returns to labor across sectors. As a result, individuals tend to reallocate labor from sectors that are more severely damaged to less vulnerable sectors. Since labor is a critical production factor, the economic and welfare implications associated with climate-induced labor reallocation are potentially quite large.

However, this potential channel through which climate change may affect economic performance and social welfare has not received the attention it deserves. The current understanding of the effect of climate change on labor allocation comes mainly from empirical studies that infer the effect of long-term climate change through examining the effect of short-lived weather fluctuations (Connolly, 2008; Graff Zivin and Neidell, 2014; Jessoe et al., 2018).[3] Considering individuals are more likely to adapt to a gradual change in climate than to idiosyncratic and short-lived weather shocks (Seo, 2013; Moore and Lobell, 2014), the *magnitude* of long-term climate change impact on labor allocation could be significantly different from short-run weather fluctuations.[4]

To fill this gap in the literature, we estimate the long-term effects of climate change on labor allocation using the "hedonic approach" (Mendelsohn et al., 1994; Mendelsohn and Massetti, 2017), which accounts for individual long-term adjustments to climate change. The hedonic approach identifies the effects by cross-sectional long-term climate differences. Since individuals on average should have enough time to fully adjust their behavior to the long-term climate of their region, the effects identified by this approach should incorporate long-term adaptation information (Mendelsohn et al., 1994). To the best of our knowledge, the current study is the first to employ the hedonic approach to identify the long-term effects of climate change on individual-level labor allocation.

A significant concern of the traditional cross-sectional hedonic approach is omitting variables. To address this concern, we adopted an improved hedonic approach that identifies the long-term effects in a panel framework. As suggest by Massetti and Mendelsohn (2011), the problem of omitted variables can be significantly reduced in a panel framework with fixed effects. In addition, we have also checked the sensitivity of our findings to omitted variables by including various control variables and found comparable results.

Depending on a panel of field survey data from 8076 working age residents in 279 rural communities in China, we find that a 1 °C increase from current mean temperature will reduce an average rural resident's time allocated to farm work by 7.0%, increase the time allocated to off-farm work by 7.8%, and reduce the time allocated to leisure by 0.8%. These findings are robust to alternative climatic measures, omitted variables, estimation methods, and the decision-making processes. We also find differential responses to climate change across gender: higher temperatures mainly shift males' time from leisure to off-farm work, but mainly shift females' time from farm work to off-farm work. Under the medium climate change scenario RCP 4.5, we predict the end-of-the-century climate change will reduce rural residents' farm work time by 15.5%, increase their off-farm work time by 17.1%. Combining these estimates with the overall labor supply in rural China, we roughly estimate that climate change will reduce the agricultural labor supply by 40.0 million people and increase the off-farm labor supply by 44.1 million people.

This article complements the preceding studies that infer the long-term effects of climate change on the labor market through examining the short-run effect of temperature shocks (Graff Zivin and Neidell, 2014; Jessoe et al., 2018).[5] These studies generally identified statistically significant effects only for changes in extreme heat (but not mean temperature) and the effects identified are very small. For example, based on the same climate change projection as the present study, Jessoe et al. (2018) predicts that increases in extreme heat will reduce the probability that a rural Mexican works in his/her home village by 0.31%. Based on the hedonic approach, which allows individuals to fully adjust their behavior to climate change in the long run, we find a much larger labor reallocation effect, mainly from changes in the mean temperature (but not extreme heat). The larger effect in the long run is intuitive, because the existence of quasi-fixed physical capital limits labor reallocation in the short run. In the next section we provide a theoretical model to explain this in detail.

This article also contributes to the literature on migration and adaptation. Previous studies have identified various determinants of rural-urban migration, such as income gaps (Carrington et al., 1996), local credit and insurance markets (Woodruff and Zenteno, 2007), and farmland property rights (Acemoglu et al., 2001). Although there is growing interest in the effect of global environmental change on migration (see,e.g., Boano et al., 2008; Black et al., 2011), rigorous empirical

[2] As will be clear in the following, the current article focuses on the effects of higher temperatures but not the effects of extreme weather events or other consequences of climate change.

[3] Labor reallocation as considered here has a broader definition than migration: it is possible for individuals to work in other sectors without migrating. For example, according to our survey (see section 3.1), 18.1% of rural residents in China have both farm and off-farm work within a year, and of those 38.8% have off-farm work within their counties.

[4] Since labor and capital are complements, the existence of quasi-fixed physical capital in the short run suggests that the long-term impact of climate change on labor reallocation could be much larger. See Dell et al. (2014) for a similar concern about translating results from short-run analyses to the long-term.

[5] Graff Zivin and Neidell (2014) examine the effects of inter-annual weather fluctuations on individual time allocation between work, indoor leisure, and outdoor leisure. Jessoe et al. (2018) examines the effects of inter-annual weather fluctuations on labor allocation and migration (both domestically and internationally) in rural Mexico.

evidence for this issue is rare (Bohra-Mishra et al., 2014).[6] We contribute to the literature by examining the size of the effect of climate change on migration. This article also contributes to the literature on climate change adaptation. Adaptation is central to the climate change impact study because it may determine the future severity of the impact (Mendelsohn et al., 1994; Lobell et al., 2008). Although various adaptation methods have been examined,[7] adaptation to climate change by time reallocation has been generally ignored.[8]

Finally, although an economy-wide structural shift from employment in agricultural to nonagricultural activities is a typical feature of the development process (Kuznets, 1955; Poston et al., 2010), the welfare implications of the climate change induced rural-urban migration could be quite different from those caused by economic development: it is not necessarily associated with improved urban labor demand. If urban areas are ill-equipped to absorb a massive influx of migrants, climate change may aggravate urban unemployment and urban poverty, which are vital concerns for some developing countries (see, e.g., Siwar and Yusof Kasim, 1997; De Janvry and Sadoulet, 2000; Cheng et al., 2002).

The rest of this article is organized as follows: Section 2 contents the theoretical framework of this article. Section 3 describes the dataset and econometric model. Section 4 presents estimation results and sensitivity checks. Section 5 concludes this paper. The online appendix provides additional robustness checks.

2. Motivating theory

This section develops a simple theoretical model to illustrate that climate change will induce labor reallocation from agriculture to non-agriculture sectors and the effect is higher in the long run than in the short run. The intuition is that climate change may have a much larger damage on agriculture than on other sectors (Hancock et al., 2007; Mendelsohn, 2008; Dellink et al., 2017),[9] and that the disproportionate damage generates a gap in marginal returns to labor between sectors and hence induces labor reallocation. In addition, since labor and capital are complements, the existence of quasi-fixed physical capital in the short run limits labor reallocation.

The model assumed a closed economy with two sectors, the climate-exposed agriculture sector $a$and the climate-insensitive non-agriculture sector b. A representative rural resident who is endowed with a unit of time chooses how to allocate it between farm work, off-farm work, and leisure to maximize its lifetime utility $U(c, s)$, which is derived from consumption (c) and leisure (s). Consumption depends on labor income from farm and off-farm work.

Agricultural production is according to a standard Cobb–Douglas production function:

$$y_a = A_a l_a^{\beta} k_a^{1-\beta} \tag{1}$$

where y_a is per capita output in the agriculture sector a, A_a is the Hicks-neutral efficiency level or *TFP*, l_a is per capita labor input, k_a is per capita farmland input, and $\beta \in (0, 1)$. For simplicity, we assume the farmland is rented from a competitive market and the rural resident does not hold the property rights.[10]

In the long run, when farmland can be seen as flexible, the rural resident's utility-maximizing problem is

$$\begin{gathered} \max_{l_a, l_b, s} U(c, s) \\ \text{s.t.} \quad c = l_a w_a + l_b (w_b - m), \quad s = 1 - l_a - l_b \end{gathered} \tag{2}$$

[6] For an overview of the literature, see Lonergan (1998) and Perch-Nielsen et al. (2008).

[7] For example, Kurukulasuriya and Mendelsohn (2008) and Wang et al. (2010) examine farmers' adaptation to climate change by switching crops, Seo and Mendelsohn (2008) examine the adaptation by switching among different kinds of livestock, Falco and Veronesi (2013) examine the adaptation by adopting water and soil conservation behaviors, and Huang et al. (2015) examine the adaptation by various farm management methods. See Massetti and Mendelsohn (2018) for a review.

[8] The current article is also remotely related to Huang et al. (2018) in the sense that they depend on the same field survey data and both examine the consequences of climate change. However, while Huang et al. (2018) examines the potential benefits (measured by gains in agricultural profits) of agricultural adaptation to long-run climate change, the current article examines the effects of long-run climate change on labor allocation between farm work, off-farm work, and leisure.

[9] The most obvious reason for the larger damage to agriculture is that farmers are more exposed to climate than workers in other sectors and climate elements are direct inputs in agricultural production. Although previous empirical studies generally find significant damages of higher temperatures on agricultural output (Schlenker and Roberts 2009; Fisher et al. 2012; Chen et al. 2016), the effects identified on non-agriculture sectors are relatively small (Somanathan et al. 2015; Donadelli et al. 2017; Zhang et al. 2018). Previous studies do find that, while climate change has no significant effect on economic growth in rich countries, warming appears to significantly reduce economic growth in poor countries (Eboli et al. 2010; Dell et al. 2008; Hsiang 2010). However, since economic performance in poor countries depends heavily on agriculture, the negative effect of warming on growth may mainly reflect the negative effect on agriculture.

[10] Assuming the rural resident as the owner of farmland will not change the qualitative implication on labor allocation. This is because the only way for the ownership of farmland to affect labor allocation is through affecting budget constraints and the return to land is a linear function of the return to labor. Specifically, according to the production function, the ratio of return to labor and land in a competitive equilibrium is $\beta/(1-\beta)$.

where l_a and l_b are time allocated to sectors a and b respectively; w_a and w_b denote wages in sectors a and b; and m measures the cost of reallocating a unit of time from sector a to sector b.[11] Note that return to farmland, $(1-\beta)y_a$, does not enter the budget constraint because it is equal to the rent paid in the competitive land market.

By normalizing the price of agricultural output into one, the agriculture wage can be measured by

$$w_a = \frac{dy_a}{dl_a} = \beta A_a l_a^{\beta-1} k_a^{1-\beta} \tag{3}$$

For simplicity, we follow the textbook model (Singh et al., 1986) to assume off-farm wage as given ($w_b = \overline{w}_b$).[12] According to the law of equi-marginal utility, the utility-maximizing condition is $dU/_{dl_a} = dU/_{dl_b} = dU/_{ds}$, which can be simplified into

$$\beta w_a = \overline{w}_b - m \quad \text{and} \quad U_c \beta w_a = 2U_s \tag{4}$$

with $U_c \equiv dU/_{dc}$ and $U_s \equiv dU/_{ds}$.[13]

Now let us turn to the short-run case and assume farmland as fixed ($k_a = \overline{k}_a$). Although farmland can be seen as flexible in the long run, it is most likely fixed in the short run. For example, the agricultural production decision is usually made before the realization of yearly weather outcome, so farmers may not be able to adjust farmland input in response to the yearly weather fluctuations. The short-run utility-maximizing problem is

$$\begin{gathered} \max_{l_a, l_b, s} U(c, s) \\ \text{s.t.} \quad c = l_a w_a + (1-\beta) A_a l_a^{\beta} \overline{k}_a^{1-\beta} - \overline{e} + l_b(\overline{w}_b - m), \quad s = 1 - l_a - l_b \end{gathered} \tag{5}$$

where $(1-\beta)A_a l_a^{\beta} \overline{k}_a^{1-\beta}$ is the return to farmland and $\overline{e}$ is the rent of farmland, which is paid before the realization of yearly weather outcome. If without uncertainty and the agricultural output is the same as predicted, we have $(1-\beta)A_a l_a^{\beta} \overline{k}_a^{1-\beta} = \overline{e}$, and the budget constraint is the same as that in the long-run case. If with unanticipated shocks, such as yearly weather shocks, the utility-maximizing conditions are:

$$\widehat{w}_a = \overline{w}_b - m \quad , \quad U_c \widehat{w}_a = 2U_s \tag{6}$$

where $\widehat{w}_a$ denotes the short-run equilibrium wage. Compared with the long-run equilibrium conditions in (4), the difference is that the output elasticity of labor (β) no longer shows up on the left-hand side of the equilibrium conditions. This is because, when adjusting agricultural labor input in response to short-run shocks, farmers have to take into account changes in returns to both labor and farmland, and the output elasticity of farmland is $1-\beta$.

We introduce the impact of climate change by rewriting agricultural production function as:

$$y_a(T) = (A_l(T) l_a)^{\beta} (A_k(T) k_a)^{1-\beta} \tag{7}$$

where Tdenotes climatic indicates, and $A_l(T)$ and $A_k(T)$ are labor and land productivities respectively. The agricultural *TFP* in (1) is the weighted average of labor and land productivities, $A_a \equiv A_l^{\beta}(T) A_k^{1-\beta}(T)$, and the weights are output elasticities of labor and land. Climate change may reduce *TFP* by damaging both labor and land productivities (Kjellstrom et al., 2009; Roos et al., 2011; Zhang et al., 2018). Whether or not the damage is through lowering $A_l(T)$ or $A_k(T)$, the marginal returns to labor, $dy_a/dl_a = w_a = \beta A_a l_a^{\beta-1} k_a^{1-\beta}$, will be reduced.

PROPOSITION 1. Climate change leads to labor reallocation from the climate-exposed sector to the climate-insensitive sector both in the long-run and short-run.

Proof. If climate change significantly reduces the marginal returns to labor (wages) in the agriculture sector $a$relative to that in the non-agriculture sector b,[14] the equilibrium conditions (4) and (6) no longer hold and we have $\beta w_a' < \overline{w}_b - m$ and $w_a' < \overline{w}_b - m$, where w_a' and $\widehat{\widehat{w}}_a$ denote agricultural wages after the damage of climate change in the long-run and short-run, respectively. Therefore, it is utility-improving for the rural resident to reallocate labor from sector $a$to sector $b$to enhance the marginal returns to agricultural labor. □

[11] The model assumes that the cost of reallocating a unit of labor is constant (m), so labor reallocation only changes the share of time each person is allocated to a certain sector (i.e., $l_a$and l_b). We can also assume that the marginal cost of labor allocation is declining with the time reallocated by each person, so that climate change changes the number of workers in each sector. However, this alternative assumption does not affect the direction of labor reallocation, which is the focus of our model.

[12] Alternatively, we can endogenize the off-farm wage by assuming the wage in the off-farm sector is a decreasing function of off-farm labor supply. Therefore, labor reallocation increases off-farm labor supply and lowers off-farm wage, which in turn affects the magnitude of labor reallocation. However, an endogenous off-farm wage will only affect the *magnitude* but not the *direction* of labor reallocation, which is the main interest of our theoretical model.

[13] $dU/_{dl_a} = U_c dc/_{dl_a} + U_s ds/_{dl_a} = U_c \beta w_a - U_s$, $dU/_{dl_b} = U_c dc/_{dl_b} + U_s ds/_{dl_b} = U_c(\overline{w}_b - m) - U_s$, $dU/_{ds} = U_s$.

[14] For simplicity, the model assumes no damage of climate change on marginal returns to labor in the non-agriculture sector (i.e., $w_b = \overline{w}_b$). As long as climate change damage on marginal returns to labor in the agriculture sector is larger than that in the non-agriculture sector, this assumption does not affect the qualitative implications of our model.

The long-run equilibrium condition after labor reallocation is

$$\beta w_a^* = \overline{w}_b - m \tag{8}$$

where w_a^* is the long-run equilibrium wage after labor reallocation.[15] The short-run equilibrium condition after labor reallocation is

$$\widehat{w}_a^* = \overline{w}_b - m \tag{9}$$

where $\widehat{w}_a^*$ is the short-run equilibrium wage.

PROPOSITION 2. The labor reallocation effect is larger in the long run than in the short run.

Proof. According to (8), (9), and (3) we have

$$\beta w_a^* = \widehat{w}_a^*\ , \qquad w_a^* = \beta A_a^* l_a^{*\beta-1} k_a^{*1-\beta}\ , \qquad \widehat{w}_a^* = \beta \widehat{A}_a^* \widehat{l}_a^{*\beta-1} \overline{k}_a^{1-\beta} \tag{10}$$

where A_a^* and $\widehat{A}_a^*$ are *TFP* after climate change in the long run and short run respectively; l_a^* and $\widehat{l}_a^*$ are labor input after labor reallocation in the long run and short run respectively; and k_a^* is the long-run farmland employed in the final equilibrium. To make the long-run and short-run labor reallocation effects comparable, we investigate the effects of the same damage of climate change (i.e., $A_a^* = \widehat{A}_a^*$). The land input should be lower in the long-run equilibrium than the short-run fixed level ($k_a^* < \overline{k}_a$) because in the long run the marginal return to land, $(1-\beta)A_a^* l_a^{*\beta} k_a^{*(-\beta)}$, is reduced due to the damage of climate change on *TFP*($A_a^* < A_a$) and the reduction of agricultural labor input ($l_a^* < l_a$).[16] Since $\beta w_a^* = \widehat{w}_a^*$ and $0 < \beta < 1$, we have $w_a^* > \widehat{w}_a^*$. Since $A_a^* = \widehat{A}_a^*$ and $k_a^* < \overline{k}_a$, we get $l_a^* < \widehat{l}_a^*$. □

3. Empirical strategy

This section presents the data and econometric model used to identify the effects of climate change on labor reallocation in rural China.

3.1. Data

3.1.1. Field survey data

Individual-level labor allocation comes from a large-scale field survey conducted in rural China in 2013. The survey collected data from 2790 households in 279 rural communities (villages) for the years 2010, 2011, and 2012. Specifically, the survey involved 31 counties in 8 provinces of China (see Fig. 1).[17] We randomly selected 3 counties from each of 7 sample provinces, but selected 10 counties from Jiangxi province because extra funding was available. We then randomly selected 3 townships from each county, 3 villages from each township, and 10 households from each village for face-to-face interviews.

During the face-to-face interviews, respondents were asked to report retrospectively the number of *weeks* each working age (defined as 18 to 60 years old) household member spent on farm work, off-farm work, and leisure in each of the years 2010, 2011, and 2012.[18] Farm work refers to all self-employed and employed work in agricultural production, off-farm work refers to all other paid non-agricultural work (for wages or self-employed), and leisure refers to the remaining time (measured in weeks). Therefore, our survey defined the three options for time allocation in a way which totals 100%. After dropping missing values, we got a sample of 8076 working age individuals from 2522 households for each year.

The seasonality of agricultural production determines that the labor allocation data for rural residents have to be collected for the whole calendar year. Intensive labor input is required in agriculture only during the growing season of crops and rural residents may allocate time to off-farm work after the growth season. According to our survey, 18.1% of rural residents in China have both farm work and off-farm work within a year. Therefore, collecting data for a sub-period of a year (such as several months or weeks) cannot capture the whole picture of rural residents' labor allocation behavior and hence may lead to a biased estimate of the effect of climate on labor allocation.

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[15] Since labor reallocation is costly ($m > 0$), farmers may first adopt less expensive within-farm adaptation measures, such as shifting crop types and changing growing seasons. Farmers will reallocate labor to off-farm work if the climate-induced gap in marginal returns to labor is larger than the cost of migration, even after adopting other feasible adaptation methods.

[16] The model assumes farmland is rented from a competitive market and its supply is not perfectly inelastic in the long run. An alternative assumption is that farmland is accumulated consumption goods. Since climate change reduces consumption, the marginal utility of consumption increases and hence the incentive to invest in farmland declines, which will also lead to a lower level of farmland input.

[17] Which provinces were included in the survey depended on funding availability.

[18] An important challenge in the collection of our data is to ensure its precision. To do so, we only required the respondents to report the data for the three years (but not a longer time) leading up to the survey year. More importantly, during the survey, if the respondents were uncertain about the information, we would require them to confirm it by contacting their spouses or employers.

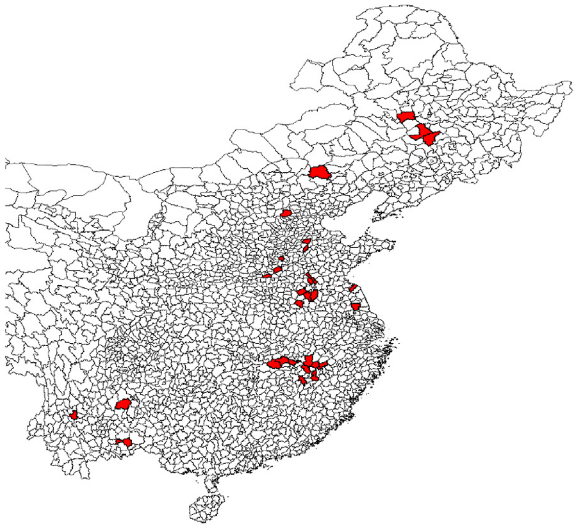

Fig. 1. Sample counties. *Note*: The figure presents the geographic location of the 31 sample counties. The number of households surveyed in each county is the same (i.e., 90). The figure shows only parts of the mainland China.

For this reason, our survey required respondents to report the number of weeks each household member allocated to farm work, off-farm work, and leisure for a given year (instead of a sub-period of a year). As a trade-off, our survey did not include the information about more detailed time allocation, such as within-day time allocation; it is almost impossible to collect daily or hourly data over the whole year in the self-reported and retrospective survey while insuring reasonable reliability. Fortunately, the main purpose of this study is to investigate the labor allocation between farm work and off-farm work, which unlikely to occur within a short time period (e.g., a day). Nevertheless, caution should be taken when interpreting our estimates about the time allocated to leisure: higher temperatures may alter within-day time allocation between work and leisure (Graff Zivin and Neidell 2014), which cannot be captured in our data.

An advantage of our survey data is that it enables us to capture within-year time reallocation. Previous studies of labor allocation and migration usually depend on yearly data that ignore this possibility, but for farmers in developing countries, within-year time reallocation may play an important role in adapting to climate change. Instead of migrating to off-farm sectors permanently, some farmers choose to reallocate part of their time from farm work to off-farm work within a year. Therefore, examine the effect of climate change on labor allocation while ignoring within-year time reallocation may underestimate the effect.

As reported in Table 2, an average working-age rural resident allocated 31.1% of their time to farm work, 33.1% to off-farm work, and 35.8% to leisure. Among the 8076 individuals surveyed, within a year, 47.3% of them had only farm work, 23.8% had only off-farm work, 18.1% had both farm and off-farm work, and the remaining 10.7% had no work. In addition, 38.8% of the off-farm jobs were within their own counties and the remaining 61.2% were outside them.

3.1.2. Climate data

We derived daily climatic measures from the China Meteorological Data Sharing Service System (http://cdc.nmic.cn), which provides daily mean temperature and total precipitation for each of the 677 meteorological stations throughout China and represents the most detailed and reliable climate dataset in China. For 22 of the sample counties that have at least one meteorological station, county-level climate measures were calculated as the inverse-distance weighting average from all the meteorological stations within the county. For the remaining 9 sample counties where meteorological stations were not available, we instead used the inverse-distance weighting average of the climate data from the stations within a radius of 100 km.[19]

The daily climate data (i.e., daily minimum temperature, maximum temperature, and precipitation) are used to construct the county-level standard climatic measures: growing season degree-days (GDDs), growing season harmful degree-days (HDDs), and growing season total precipitation (GTP). GDDs measures the cumulative exposure to heat between 8°C and 32°C during the growing season (April—September) of major crops. We follow Schlenker and Roberts (2009) to approximate the distribution of temperatures within each day using a sinusoidal curve between minimum and maximum temperatures. We then applied the sinusoidal approximation to calculate the time that counties were exposed to each 1°C temperature

[19] First, we choose a circle with a 100 km radius for each county's centroid. Second, we take the weighted average of the climate data for all stations within the circle, where the weights are the inverse of the distance between each station and the county's centroid. Finally, we assign the weighted average to each county.

Table 1
Definition of variables.

Variables	Definition
Time allocation:	
Time allocated to farm work	Percentage of time each working age ($18 \le age \le 60$) person spends on farm work (%)
Time allocated to off-farm work	Percentage of time each working age ($18 \le age \le 60$) person spends on off-farm work (%)
Time allocated to leisure	Percentage of time each working age ($18 \le age \le 60$) person spends on leisure (%)
Climatic variables:	
Growing season degree-days	The sum of degree-days from April to September
Growing season harmful degree-days	The sum of harmful degree-days from April to September
Growing season total precipitation	Total precipitation from April to September (mm)
Other variables: [b]	
Sunshine duration	Hours
Relative humidity	%
Wind speed	m/s
Evaporation	mm
Soil quality	County-level land quality measured by loam in the soil (%)[a]
Non-agricultural wage	County-level average wage of non-agricultural staff and workers (2010 constant 1000 yuan/year)
GDP per capita	Real GDP per capita in 2010 constant value (Yuan)
GDP share of agriculture	The share of agriculture in GDP
Investment ratio	The investment to GDP ratio
Per capita farmland	Per capita farmland (ha)

[a] Loam is a standard indicator of soil quality. Loam is considered ideal for agricultural uses because it retains nutrients well and retains water, while still allowing excess water to drain away. The data come from the Resources and Environment Data Center of Chinese Academy of Sciences (http://www.resdc.cn/).

[b] The data for all climatic variables are derived from the China Meteorological Data Sharing Service System. The data for the five economic variables listed at the last five rows are derived from the *China Statistical Yearbook for Regional Economy*.

interval within each day. Finally, the GDDs is calculated by summing up the time under each 1°C interval across the growth season according to the following rules: a day (24 h) exposed to a temperature (say $\bar{z}$) below 8°C contributes 0 degree-days, between 8°C and 32°C it contributes $\bar{z} - 8$ degree-days, and above 32°C it contributes 24 degree-days.

Alone, GDDs may not accurately account for the effect of extremely high temperatures on agricultural yields and hence on labor allocation. Studies that examine the nonlinear effects of temperature suggest that crop yields decrease sharply for mean temperatures above a harmful threshold (see, e.g., Schlenker and Roberts 2009). A measure used to capture the harmful effects of extremely high temperatures is HDDs, and it is calculated as the sum of degree-days above a harmful threshold, which is usually set as 32°C. Thus, a day (24 h) exposed to a temperature (say $\bar{z}$) above 32°C contributes $\bar{z}-$ 32 HDDs; otherwise, it contributes 0 HDDs. The within-day temperature distribution is also approximated using a sinusoidal curve. Finally, GTP is the total precipitation in inches during the growing season. In this analysis, all climate variables are calculated as the average for the 30 years up to the survey year. For example, GDDs for county k in 2010 is the average GDDs from 1981 to 2010. The summary statistics of climatic variables are also reported in Table 2.

Notice that we define growing season as from April to September for all counties because the major crops (i.e., rice, wheat, maize, and soybean) are mainly grown during these months in China. However, this definition is imprecise for two reasons. First, the exact sowing and harvesting dates differ across regions and across major crops. Second, according to our survey, farmers usually plant multiple crops in sequence in a plot within a year, with the main growing season used for the major crops, while other seasons for minor crops, such as oilseed rape, beans, and vegetables.[20] We adopt two robustness tests to check if our main findings are robust to the definition of the growing season. Specifically, Columns (1a)–(1c) of Table A1 provide estimates based on yearly climatic measures and Columns (2a)–(2c) of Table 7 provide estimates based on county-specific growth seasons defined according to the most extensively planted crop in each county.

Although the most frequently examined climatic variables in climate change impact studies are temperature and precipitation, Zhang et al. (2017) highlight the importance of other climatic variables based on meteorological station data from China. Following Zhang et al. (2017), we derived four additional climatic variables (i.e., relative humidity, wind speed, sunshine duration, and evaporation) from the China Meteorological Data Sharing Service System. These additional climatic variables will be used as control variables in the analysis.

3.2. Methodology

The model used to identify the long-term effects of climate change on the time allocation of rural residents is presented by equations 11–13. In these equations, l^f_{ikt}, l^o_{ikt}, and l^l_{ikt} are dependent variables that denote the percentage of time adult i in county k and year t allocate to farm work, off-farm work, and leisure, respectively; $\overline{C}_{kt}$ is a vector of county-level standard

[20] According to the survey, multiple planting in sequent seasons is a common practice in middle and low latitudes of China, and in some provinces, plants are usually growing in every season of the year. For example, farmers in Yunnan province usually plant potatoes in the same plots after harvesting rice each September, while farmers in Jiangxi province plant oilseed rape from January to April before the temperature is high enough for other crops.

Table 2
Summary statistics of variables.

	Mean	Standard deviation
Time allocation of an average adult:		
Time allocated to farm work (%)	31.1	32.0
Time allocated to off-farm work (%)	33.1	39.5
Time allocated to leisure (%)	35.8	31.9
Employment status of the whole sample (8076 adults)		
Farm work only (%)	47.3	N/A
Off-farm work only (%)	23.8	N/A
Both farm and off-farm works (%)	18.1	N/A
No work (%)	10.7	N/A
Climatic variables:		
Growing season degree-days (100 degree-days)	31.4	6.6
Growing season harmful degree-days (degree-days)	20.1	25.7
Growing season total precipitation (100 mm)	9.3	4.8
Other variables:		
Sunshine duration (hours)	6.2	1.1
Relative humidity (%)	72.4	7.8
Wind speed (m/s)	2.5	0.7
Evaporation (mm)	5.3	0.8
Soil quality (index)	30.4	4.5
Non-agricultural wage (1000 yuan)	35.5	5.2
GDP per capita (1000 yuan)	16.1	9.4
GDP share of agriculture	0.2	0.1
Investment ratio	0.7	0.3
Per capita farmland (ha)	0.1	0.1

Note: All climatic variables are calculated as the average for the 30 years up to the survey year. All other variables are the average across the three sample years. The definitions of variables are provided in Table 1.

climate variables (see, e.g., Schlenker et al. 2006; Burke and Emerick 2016) including growing season degree-days (GDDs), growing season harmful degree-days (HDDs), growing season total precipitation (GTP).[21] All climatic variables are calculated as the 30-year average prior to the survey years. The expressions μ^f_{ikt}, μ^o_{ikt}, and $\mu^l_{ikt}$are error terms.

$$l^f_{ikt} = \overline{C}'_{kt}\alpha_1 + M'_{kt}\rho_1 + \tau_p + \upsilon_t + \mu^f_{ikt} \tag{11}$$

$$l^o_{ikt} = \overline{C}'_{kt}\alpha_2 + M'_{kt}\rho_2 + \tau_p + \upsilon_t + \mu^o_{ikt} \tag{12}$$

$$l^l_{ikt} = \overline{C}'_{kt}\alpha_3 + M'_{kt}\rho_3 + \tau_p + \upsilon_t + \mu^l_{ikt} \tag{13}$$

The long-term average of climatic variables eliminates all inter-annual weather fluctuations and hence the variations used to identify the climatic coefficients are the cross-sectional long-term climate differences. Since individuals on average should have fully adapted to the long-term climate of their region (Mendelsohn et al. 1994), the climatic coefficients identified in the model reflect the long-term effects of climate change on labor allocation.

Although advanced in incorporating the long-term effects, a major concern of employing cross-sectional climatic variation is omitting variables. For this reason, we estimate the long-term effects in a panel framework instead of the traditional cross-sectional model. It is well understood that cross-sectional models are vulnerable to misspecifications (Deschênes and Greenstone 2007), but the problem can be significantly reduced in a panel framework with fixed effects (FE) (Massetti and Mendelsohn 2011). Our panel model includes province FE, τ_p, to account for inter-province long-term differences, and include year FE, υ_t, to account for the inter-annual variations that are common across regions.

We would like to highlight that, even after including these FEs, the cross-sectional climate variation in the model is large enough to identify meaningful climatic coefficients.[22] We regressed each climate variable on a full set of province FEs and year FEs to determine the remaining climate variation from the error term, which are the variations used to identify the climate coefficient in our model. For GDDs, we find the standard deviation of the remaining variation is 295 degree-days (recall the mean GDDs in our sample is 3140 degree-days). In addition, we have 29% samples with the remaining GDDs (in absolute value) greater than 200 degree-days, and 64% greater than 100 degree-days. Similarly, the standard deviation of the remaining variation for HDDs and GTP are 5.2 degree-days and 230 mm respectively, which are quite large relative to their sample means, as reported in Table 2.

[21] As robustness checks, various alternative linear and non-linear temperature measures were also tried. See Fig. 2 and Table 5 for details.

[22] Although province fixed effects enable us to account for province-level time invariant confounding factors, they eliminate inter-province climate differences. However, as a robustness check in Columns (2a)–(2c) of Table 3, excluding province fixed effects did not change our main finding.

In order to employ cross-sectional climate differences to identify the long-term effects of climate change, our model does not include county or individual fixed effects (FE) because they will eliminate all of the county-level long-term climate differences. Therefore, although inter-province long-term differences and inter-annual fluctuations are well controlled by FE, we do not control for within-province inter-county confounding factors by FE. To test the potential effect of omitted variables, we include a vector of county-level control variables, M_{kt}, that may have effects on labor allocation.[23] These control variables are sunshine duration, relative humidity, wind speed, evaporation, soil quality, non-agricultural wage, GDP per capita, the share of agriculture in GDP, the investment to GDP ratio, and per capita farmland. The definition, data source, and summary statistics of each are presented in Tables 1 and 2. These control variables are described when introduced in the analysis.

In fact, we generally believe that omitted factors should not be a major concern in the context of identifying the long-term effects of climate change. Specifically, for factors that are uncorrelated with climate, omitting them will not bias the estimated climatic coefficients. In addition, factors that are correlated with climate are most likely the outcomes but not the reasons for climate; therefore, omitting these factors should not cause a bias because the effects of climate through these factors reflect the consequences of adaptation to climate. For example, agricultural production patterns,[24] which are correlated with both agricultural labor demand and climate, are most likely the consequences of farmers' utility-maximizing choices in adapting to the climate of their regions. Since incorporating adaptation is required when inferring the long-term effects, excluding climate-dependent variables from the model will facilitate identifying long-term effects.

4. Results

In this section, we first provide the baseline estimates (subsection 4.1). We then conduct various tests to show the robustness of the baseline findings (subsections 4.2–4.4). Finally, we project the overall impacts (subsection 4.5). More robustness tests can be found in the online appendix. As the outcome variables (time allocated to farm work, off-farm work, and leisure) in the model are strongly correlated, equations 11–13 are estimated jointly in a seemingly unrelated regression (SUR) setting which allows the errors to be correlated across equations.[25]

4.1. Baseline results

The baseline results are reported in Table 3. In order to show the importance of control variables in the model, we gradually increase the number of control variables from column (1) to column (4). Specifically, column (1) includes no control variables, column (2) controls for only year fixed effects, column (3) further controls for province fixed effects, and column (4) further controls for four additional climatic measures (i.e., relative humidity, wind speed, sunshine duration, and evaporation). Although all these specifications suggest that higher GDDs significantly shift farmers' time from farm work and leisure to off-farm work, the estimated sizes of the effect are quite different. The largest labor reallocation effect is found in column (4), which includes the most complete set of control variables.

As discussed above, estimates in column (1) are potentially confounded by inter-annual fluctuations, long-run differences across provinces, and other climatic variables. By controlling for inter-annual fluctuations using year fixed effects, column (2) finds a larger effect of GDDs on reallocating time from farm work to off-farm work. By further controlling for long-run differences across provinces using province fixed effects, column (3) finds an even larger labor reallocation effect from farm work to off-farm work. Finally, when additionally controlling for another four climatic measures in column (4), the estimated labor reallocation from farm work to off-farm work increases further. Therefore, models that omit these important controls (i.e., fixed effects and climatic controls) tend to underestimate the effect of warming the labor reallocation.[26] In the online appendix (Table A2), we show that the estimates in column (4) are robust when we include higher-order measures of the four climatic controls. In addition, Table A2 also shows that the pattern of effects is the same when we include the interaction terms between GDDs and the four climatic controls. Therefore, we consider the results in column (4) as those of our baseline model. All the following robustness checks are based on the baseline model.

The baseline estimates suggest that a 1°C increase from current mean temperature (approximately equal to 240 unit increases in GDDs) will reduce an average rural resident's time allocated to farm work by 7.03%, increase the time allocated to off-farm work by 7.82%, and reduce the time allocated to leisure by 0.79% (statistically insignificant). This finding is consistent

[23] We also tried to include various household- and individual-level control variables (such as age, gender, and dependency ratio, which are available from our survey), but find quite similar results. We prefer to exclude these micro-level control variables from our analysis because it is difficult to believe that these micro-level factors could be associated with county-level climate variations.

[24] Agricultural production pattern refers to the combination of agricultural production behaviors, including the choice of crop types, growing seasons, and cultivation patterns.

[25] Since the model as expressed in – is singular, it was estimated by dropping one equation each time. Specifically, the coefficients for the three equations were obtained by first estimating equations (1) and (2) together and then estimating equations (2) and (3) together. In fact, estimating each equation separately will obtain similar results because the time allocations sum to 100% for each person and the control variables are the same across models (Wooldridge 2002; StataCorp 2011).

[26] A potential concern of the model including province fixed effects is that it eliminates the long-term climatic differences between provinces and thus may reduce the estimation efficiency. However, comparing the estimates from column (2) with those from column (3), we find that including province fixed effects does not reduce the significance level of the estimated effects. This result suggests that we have large enough within-province climatic variation for identifying the coefficients.

Table 3
The effects of climate change on labor allocation (%).

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−0.50*	3.59***	−3.09***	−0.80**	2.15***	−1.35***	−1.20**	1.37***	−0.16	−2.93***	3.26***	−0.33
	(0.30)	(0.36)	(0.30)	(0.35)	(0.42)	(0.35)	(0.37)	(0.45)	(0.37)	(0.46)	(0.56)	(0.46)
HDDs	−0.04***	−0.08***	0.12***	−0.01	−0.05***	0.06***	0.01	−0.04*	0.03*	0.05***	−0.08***	0.03*
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
GTP (100 mm/year)	−0.05	0.31***	−0.26***	−0.27***	0.69***	−0.42***	−0.67***	0.76***	−0.09	−0.10	−0.04	0.14*
	(0.05)	(0.06)	(0.05)	(0.06)	(0.08)	(0.06)	(0.11)	(0.14)	(0.11)	(0.07)	(0.09)	(0.07)
Sunshine duration (h)										−6.70***	4.91***	1.79***
										(0.68)	(0.83)	(0.67)
Relative humidity (%)										−0.39***	0.85***	−0.46***
										(0.11)	(0.13)	(0.11)
Wind speed (m/s)										0.45	−0.41	−0.04
										(0.44)	(0.55)	(0.44)
Evaporation (mm)										3.49***	−2.40***	−1.10*
										(0.57)	(0.70)	(0.57)
Province fixed effects							Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228

Note: Columns (1a)–(1c) include no control variables, columns (2a)–(2c) control for year fixed effects, columns (3a)–(3c) further control for province fixed effects, and columns (4a)–(4c) further control for four additional climate measures. Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

with the fact that agriculture is generally more vulnerable to high temperatures than non-agriculture sectors (Hancock et al. 2007; Mendelsohn 2008; Dellink et al. 2017).[27]

Contrary to the effect of GDDs, the baseline estimates suggest that higher HDDs shift farmers' time from off-farm work to farm work and leisure. It is natural that higher HDDs increase leisure because extreme heat discourages work by causing discomfort and fatigue (González-Alonso et al. 1999; Ramsey 1995; Pilcher et al. 2002). A potential reason for higher HDDs to reallocate time from off-farm work to farm work is that the off-farm works available for farmers are mainly climatic-exposed manual labor; at extreme heat, farmers may suffer more from the off-farm manual labor than from farm work (which they can flexibly choose the working hours). However, because the effect size of HDDs is much smaller relative to that of GDDs, the overall effect of warming is dominated by the effect of GDDs (we return to this in section 4.5). Finally, the baseline estimates suggest that the effects of GTP are extremely small and mainly statistically insignificant.

4.2. Channel variables

Our baseline model does not include control variables except the four climatic controls. This is because, as explained before, if the control variables are correlated with climate, it is likely that they are caused by climate. In other words, these control variables may be the channels through which climate affects labor allocation. As such, controlling for them could partly account for the true effect of climatic variables. Table 4 examines the effect of including six potential channel variables in the baseline model: soil quality, per capita farmland, non-agricultural wage, GDP per capita, the share of agriculture in GDP, and the investment to GDP ratio. From columns (1) to (6) we gradually add the six control variables one by one. Column (7) controls for the interactions between GDDs and the six control variables. The definition and summary statistics of these control variables are presented in Tables 1 and 2.

We find that controlling for soil quality (column 1) and per capita farmland (column 2) has only small effects on the estimated effects of GDDs and HDDs (compared with the baseline estimates). However, controlling for non-agricultural wage (column 3) and GDP per capita (column 4) significantly reduces the estimated effects. For example, controlling for GDP per capita reduces the marginal effect of GDDs on farm work from -2.93 to -2.17, and makes the effect of HDDs on farm work smaller and statistically insignificant. Columns (5) and (6) show that additionally controlling for the share of agriculture in GDP and the investment to GDP ratio have only small effects. Therefore, we identified non-agricultural wage and GDP per capita as two important channel variables. Column (7) shows that controlling for the interactions between GDDs and the six control variables does not change the effect pattern of GDDs, although the effect size of GDDs is not directly interpretable.[28]

[27] Farmers are more exposed to climate than workers in other sectors, and climate elements are direct inputs in agricultural production. Table A3 supports this point by demonstrating that lower agricultural profits shift labor from farm work to off-farm work.

[28] Since the interaction term of GDDs is included in the model, the estimated coefficient of GDDs indicates its effect on labor allocation when the value of the variable interacted with it (e.g., evaporation) equals zero, which is obviously not realistic.

4.3. Non-linear effects of temperature

This subsection explores the non-linear effects of temperature on labor allocation by estimating a flexible model and a piece-wise model.

4.3.1. The flexible model

An assumption of the baseline model is that the relationship between temperature and labor allocation is linear. We now relax this assumption and follow the literature (see, e.g., Schlenker and Roberts, 2009; Graff Zivin and Neidell, 2014) to try a flexible measure of temperature. Specifically, we use county-level daily minimum and maximum temperatures to construct 3 °C bins ranging between 8 °C and 32 °C (e.g., 8–11, 11–14) and measure temperature as the number of days (24 h) that the temperature falls within each bin. We also include a bin for temperature below 8 °C and a bin for temperature above 32 °C. The within-day temperature distribution is also approximated using a sinusoidal curve. We then estimate the modified

Table 4
The effects of channel variables.

	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)	(3a)	(3b)	(3c)	(4a)	(4b)	(4c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−2.83***	3.02***	−0.19	−3.08***	3.44***	−0.36	−2.72***	2.78***	−0.06	−2.17***	2.99***	−0.82
	(0.47)	(0.57)	(0.47)	(0.53)	(0.64)	(0.52)	(0.53)	(0.65)	(0.53)	(0.56)	(0.69)	(0.56)
HDDs	0.05***	−0.08***	0.03	0.03*	−0.06***	0.03	0.03	−0.05**	0.02	0.02	−0.05**	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
GTP (100 mm/year)	−0.13*	0.05	0.08	−0.10	−0.03	0.12	−0.22**	0.19*	0.02	−0.24***	0.18	0.06
	(0.08)	(0.10)	(0.08)	(0.09)	(0.11)	(0.09)	(0.09)	(0.11)	(0.09)	(0.09)	(0.11)	(0.09)
Soil quality	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Per capita farmland				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-agricultural wage							Yes	Yes	Yes	Yes	Yes	Yes
GDP per capita										Yes	Yes	Yes
GDP share of agriculture												
Investment ratio												
Four climatic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228

	(5a)	(5b)	(5c)	(6a)	(6b)	(6c)	(7a)	(7b)	(7c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−2.14***	2.88***	−0.73	−2.03***	2.91***	−0.88	−16.64***	14.35***	2.29
	(0.56)	(0.69)	(0.56)	(0.57)	(0.70)	(0.57)	(3.75)	(4.58)	(3.74)
HDDs	0.02	−0.05**	0.03*	0.02	−0.06**	0.04**	−0.01	−0.08***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
GTP (100 mm/year)	−0.24***	0.18	0.06	−0.25***	0.18	0.07	−0.36***	0.52***	−0.16
	(0.09)	(0.11)	(0.09)	(0.09)	(0.11)	(0.09)	(0.10)	(0.12)	(0.10)
Soil quality	Yes	Yes	Yes	Yes	Yes	Yes			
Per capita farmland	Yes	Yes	Yes	Yes	Yes	Yes			
Non-agricultural wage	Yes	Yes	Yes	Yes	Yes	Yes			
GDP per capita	Yes	Yes	Yes	Yes	Yes	Yes			
GDP share of agriculture	Yes	Yes	Yes	Yes	Yes	Yes			
Investment ratio				Yes	Yes	Yes			
GDDs × Soil quality							Yes	Yes	Yes
GDDs × Per capita farmland							Yes	Yes	Yes
GDDs × Non-agricultural wage							Yes	Yes	Yes
GDDs × GDP per capita							Yes	Yes	Yes
GDDs × GDP share of agriculture							Yes	Yes	Yes
GDDs × Investment ratio							Yes	Yes	Yes
Four climatic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228	24,228

Note: From column (1) to column (6) we gradually add the six potential channel variables one by one. Column (7) controls for the interactions between GDDs and the six channel variables. Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

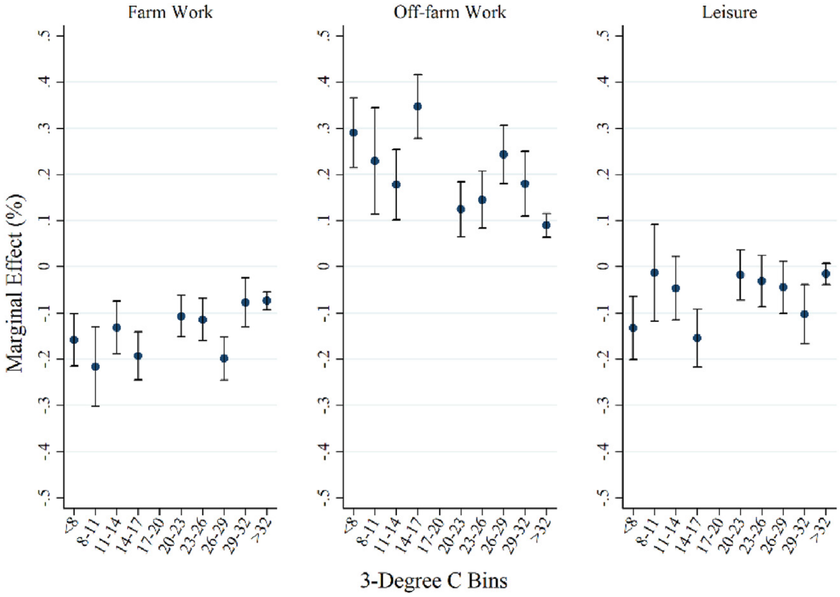

Fig. 2. Marginal Effect of 3 °C Temperature Bins on Time Allocated to Farm Work, Off-farm Work, and Leisure. *Note*: Capped spikes indicate 95% confidence interval based on standard errors clustered at the county level.

baseline model that replaces GDDs and HDDs with these bins.[29] Fig. 2 presents the marginal effect of each bin relative to a growing-condition base bin of 17°C–20 °C, within which the growing season mean temperature (19.8 °C) falls. Consistent with our baseline estimates, it shows that higher temperatures reduce time allocated to farm work, increase time allocated to off-farm work, and reduce time allocated to leisure.

Consistent with our baseline assumption, we do not find an obvious nonlinear effect of warming on labor reallocation in Fig. 2. However, because the mean and standard deviation of the marginal effect vary across temperature bins, there could be nonlinear effects concealed by the large standard deviations. To further detect the potential nonlinear effect, Fig. 3 multiplies the marginal effects presented in Fig. 2 with the relative standard deviations. It confirms that the effect of temperature on labor reallocation is not obviously nonlinear. A potential explanation for this finding is the different directions of the effect of GDDs and HDDs, as presented in the baseline estimation. For example, the positive effect of increases in GDDs on the time allocated to off-farm work can offset the negative effect of increases in HDDs and therefore result in a smaller and linear overall effect.

4.3.2. The piece-wise model

As presented in Figs. 2 and 3, the flexible model suggests no obvious non-linear effects of temperature on time allocation, although the effects are slightly different at the high-end of the temperature distribution. To further confirm this observation, we follow the literature (e.g., Schlenker and Roberts, 2009; Burke and Emerick, 2016) to estimate a piece-wise model that allows the linear relationship to change in slope above a threshold. Specifically, we loop over all possible thresholds (separately for farm work, off-farm work, and leisure), estimate the least-squares segment slopes for each one, and pick the threshold and segment slopes with the best fit. The identified thresholds for farm work, off-farm work, and leisure are all very close to the maximum GDD in our sample. As presented in Table 5, we find that before the thresholds, the effects of GDDs on time allocation are quite similar to that reported in the baseline model. After the thresholds, higher temperatures slightly reduce farm work and slightly increase off-farm work and leisure. Therefore, the piece-wise model also shows no obvious nonlinear effect.

4.4. Additional robustness checks

This subsection provides four additional robustness checks: the first calculates the long-run climatic variables in different ways; the second uses more accurate measures of growing seasons; the third focuses on the effects of degree-days during the non-busy season; and the fourth estimates the model separately for males and females. The online appendix provides checks on the sensitivity to alternative temperature measures, estimation methods, and decision-making processes.

[29] We only use this approach as a tentative test because this kind of model is potentially problematic due to multicollinearity among the temperature bins (Carter et al. 2018).

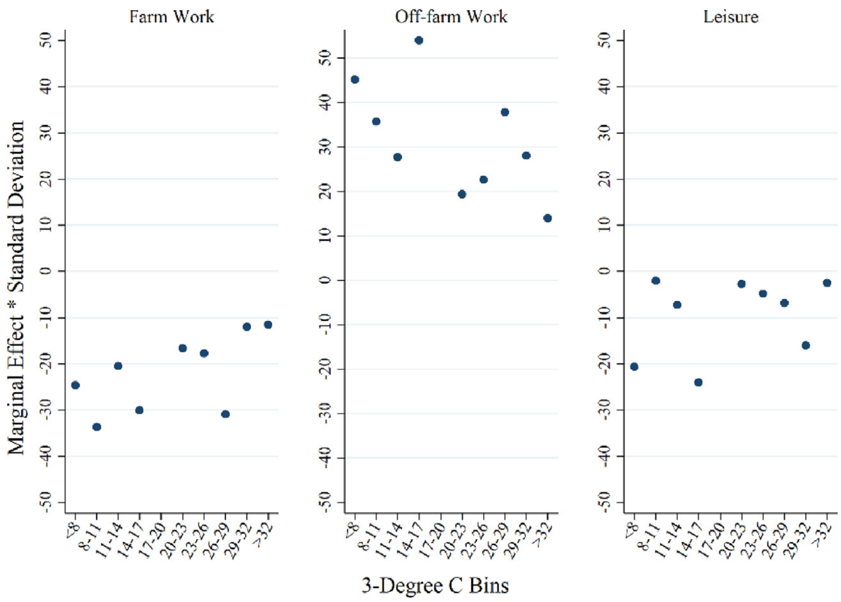

Fig. 3. Marginal Effect Multiplies the Standard Deviation. *Note*: In this figure, the marginal effects presented in Fig. 2 are multiplied by the relative standard deviations to detect potential non-linear effects.

4.4.1. The calculation of long-term climatic measures

Our baseline model calculates all climatic variables as 30-year average. It is possible that the effect of climate on labor allocation depends on the time span of the climatic variable. For example, it is possible that a farmer's time allocation is more sensitive to the recent climate conditions because of access to more employment choices. Or perhaps the earlier historical climate has a bigger impact because greater degrees of vulnerability in agriculture. We verify this possibility by calculating the climatic variables as the 10-year average prior to the survey year. As presented in Columns (1a)–(1c) of Table 6, although the effect patterns are the same as that in the baseline model, we find that the effect sizes of GDDs are slightly smaller. This finding suggests that farmer's time allocation is more sensitive to the early climate. We have also tried to calculate the climatic variables as 20-year average and found results more similar to the baseline results (omitted to save space).

Columns (2a)–(2c) calculate the climatic variables as the 30-year average from 1981 to 2010 (instead of the average of the 30 years prior to the survey years, i.e., 1981–2010, 1982–2011, and 1983–2012). Notice that the baseline specification includes province fixed effects and therefore the remaining variations in 30-year climate averages are eventually derived from the variations in 1981–1982 and 2010–2012 across provinces, together with the 30-year climate averages at the county-level within each province. This robustness check removes the variations in 1981–1982 and 2010–2012 across provinces so that the estimation depends solely on the within-province differences of the 30-year climate averages. The estimated effects of GDDs and HDDs are quite similar to those of the baseline model.

4.4.2. More accurate measures of growing seasons

Our baseline model roughly defines the growing season as from April to September for all counties. As discussed before, although this is the major period of crop production in China, the exact growing season could be different across counties. However, identifying an exact growing season for each county is difficult primarily because farmers plant multiple crops in sequence in a plot within a year. As an alternative, here we adopt more accurate growing seasons calculated based on the sowing and harvesting dates of major crops in each county. Specifically, we define growing season as from the average sowing date to the average harvesting date of the most extensively planted crop in each county (based on the harvesting area).[30] As presented in Columns (1a)–(1c) of Table 7, adopting this alternative definition of growing season does not significantly alter the estimated coefficients. The on-line appendix A1 also provides a model in which climatic variables are calculated as annual averages (and thus not subject to the choice of growing season), which finds comparable results.

4.4.3. Seasonal differences

It is also possible that farmers shift their off-farm time across seasons within the year due to either the needs of a farm-busy season or other climate adaptation behaviors. Even though the seasonal shift of farmer's labor allocation cannot be

[30] For example, the most extensively planted crop in the Poyang county, Jiangxi province is rice, and an average farm cultivates it from 18 April to 15 September. Therefore, the growing season in Poyang is defined as from 18 April to 15 September.

Table 5
The piece-wise model estimates.

	Time allocation (%)		
	Farm work	Off-farm work	Leisure
GDDs before the threshold	−2.66***	3.15***	−0.49
	(0.48)	(0.65)	(0.35)
GDDs after the threshold	−0.70**	0.31	0.39
	(0.33)	(0.22)	(0.22)
HDDs	0.07***	−0.08***	0.01
	(0.03)	(0.02)	(0.01)
GTP (100 mm/year)	−0.12	−0.01	0.13*
	(0.07)	(0.09)	(0.06)
Four climatic controls	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	24,228	24,228	24,228

Note: Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 6
Sensitive to the calculation of climatic variables.

	Time allocation (%)			Time allocation (%)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−2.24***	1.91***	0.33	−2.83***	3.02***	−0.19
	(0.48)	(0.58)	(0.47)	(0.47)	(0.57)	(0.47)
HDDs	0.03**	−0.04**	0.01	0.05***	−0.08***	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
GTP (100 mm/year)	−0.31***	0.38***	−0.07	−0.13*	0.05	0.08
	(0.08)	(0.10)	(0.08)	(0.08)	(0.10)	(0.08)
Four climatic controls	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228

Note: Columns (1a)–(1c) calculate all climatic variables as 10-year average, and columns (2a)–(2c) calculate the climatic variables as the 30 years average from 1981 to 2010 (instead of the 30 years prior to the survey years). Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 7
Sensitive to growing seasons.

	Time allocation (%)			Time allocation (%)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−2.39***	2.56***	−0.17			
	(0.26)	(0.32)	(0.26)			
Non-busy season GDDs (100 degree-days)				−1.93**	2.96***	−1.03
				(0.91)	(1.12)	(0.91)
HDDs	0.08***	−0.11***	0.03*	0.02	−0.04	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
GTP (100 mm/year)	−0.13*	−0.00	0.13*	−0.76***	0.66***	0.11
	(0.07)	(0.09)	(0.07)	(0.11)	(0.14)	(0.11)
Four climatic controls	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228

Note: Columns (1a)–(1c) adopt county-specific growing season, and columns (2a)–(2c) examine the effects on non-busy seasons. Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8
Sensitive to the calculation of climatic variables.

	Male time allocation (%)			Female time allocation (%)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
	Farm work	Off-farm work	Leisure	Farm work	Off-farm work	Leisure
GDDs (100 degree-days)	−1.31***	3.77***	−2.46***	−1.69***	2.27***	−0.58
	(0.42)	(0.49)	(0.44)	(0.65)	(0.80)	(0.58)
HDDs	0.00	−0.14***	0.13***	0.02	−0.01	−0.01
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
GTP (100 mm/year)	−0.21***	0.39***	−0.19**	−0.11	0.18	−0.07
	(0.07)	(0.09)	(0.08)	(0.11)	(0.14)	(0.10)
Four climatic controls	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,228	24,228	24,228	24,228	24,228	24,228

Note: Columns (1a)–(1c) focus on males, while Columns (2a)–(2c) focus on females. Standard errors clustering at the county level are reported in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

directly captured in this study because we depend on yearly total labor allocation data, it can be detected by dividing the yearly degree-days into a busy season and a non-busy season within the year. The growing season of major crops (April to September) can be regarded as the busy-season of agricultural production. As such, we can interpret our baseline estimates as the effects of climate during the busy-season.

We define the non-busy season as the months outside the growing season of major crops and calculate the total degree-days during the non-busy season, according to the same method as detailed in section 3.1.2. As presented in columns (2a)–(2c) of Table 7, we find that higher temperatures during the non-busy season also significantly shift labor from farm work to off-farm work. But the labor-shifting effect of GDDs in the non-busy season is much smaller than that in the busy season (which can be found in Columns (4a)–(4c) of Table 3). Considering that the total degree-days over the non-busy season is only about half of that over the busy season (i.e., the non-busy months are colder), the overall effect of warming during the non-busy season could be even smaller than that during the busy season. However, since temperatures are generally correlated over months (i.e., counties warmer in January are generally hotter in July), the effect of warming detected during the non-busy season may partly capture the effect of warming during the busy season, especially because we adopt yearly total labor allocation data.

4.4.4. Gender differences

We also investigate the different responses by gender, which is a standard issue in labor economics. We estimate the baseline model separately for males and females and report the results in Table 8. We find significant gender differences in the labor reallocation effect of warming: higher temperatures mainly shift males' time from leisure to off-farm work, but mainly shift females' time from farm work to off-farm work. In other words, warming has small effects on males' farm work and females' leisure. In addition, we find higher HDDs shift males' time from off-farm work to leisure, but have no effects on females' time allocation. The gender differences have important implications for labor structure and welfare: climate change will increase the share of males' labor in agriculture and lead to a larger loss in males' welfare (through reducing leisure).

4.5Projected overall effects of climate change

We combine the baseline estimates of GDDs and HDDs with climate change projections to simulate the overall effects of climate change on labor allocation in rural China. We do include GTP in the simulation because its effect is small and statistically insignificant. The climate projection comes from the Community Climate System Model 4 (CCSM4), one of the most widely used high-resolution climate prediction models (Taylor et al. 2012). The model provides global daily temperature and precipitation projections at a spatial resolution of 0.25 degrees × 0.25 degrees over the period 2006–2100 under various climate change scenarios. We consider climate projections under the scenarios RCP2.6, RCP4.5, and RCP8.5.

We first map the gridded daily data into each sample province to obtain province-level climate projections.[31] We then construct province-level GDDs and HDDs. Finally, we calculate climate change as the difference between the 2006–2010 average and the 2096–2100 average. As presented in column (1) of Table 9, the predicted changes in GDDs (in 100 degree-days) are 3.10, 5.45, and 13.85 respectively for scenarios RCP2.6, RCP4.5, and RCP8.5. The predicted changes in HDDs are 3.36, 8.08, and 86.43 for each of the three scenarios. Notice that the predicted increase in HDDs under the RCP8.5 is 10 times larger than that under the RCP4.5.

[31] The spatial resolution of climate predictions does not allow us to calculate the county-level predictions.

Table 9
Projected impacts of climate change.

	Projected changes in			
	(1) Climate	(2) Farm work (%)	(3) Off-farm work (%)	(4) Leisure (%)
Panel A: RCP2.6				
GDDs (100 degree-days)	3.10***	−9.07***	10.11***	−1.03
	(0.89)	(1.42)	(1.74)	(1.42)
HDDs	3.36***	0.18***	−0.28***	0.10
	(1.06)	(0.06)	(0.07)	(0.06)
Overall effect		−8.89***	9.83***	−0.93
		(1.39)	(1.71)	(1.39)
Panel B: RCP4.5				
GDDs (100 degree-days)	5.45***	−15.95***	17.77***	−1.82
	(0.45)	(2.50)	(3.07)	(2.49)
HDDs	8.08***	0.43***	−0.67***	0.24
	(2.59)	(0.13)	(0.16)	(0.13)
Overall effect		−15.52***	17.09***	−1.58
		(2.43)	(2.98)	(2.42)
Panel C: RCP8.5				
GDDs (100 degree-days)	13.85***	−40.54***	45.15***	−4.62
	(2.20)	(6.35)	(7.79)	(6.33)
HDDs	86.43***	4.65***	−7.21***	2.57
	(26.5)	(1.43)	(1.76)	(1.43)
Overall effect		−35.90***	37.94***	−2.05
		(5.69)	(6.98)	(5.67)

Note: Climatic measures are derived from the daily climate projection of CCSM4. Climate change (column 1) is calculated as the difference between the 2006–2010 average and the 2096–2100 average. Standard errors are reported in parentheses. Significance levels are *p < 0.1; **p < 0.05; ***p < 0.01.

Columns (2)–(4) of Table 9 report the projected effects of climate change on labor allocation, which is calculated by plugging the end-of-the-century climate projections into the baseline climatic estimates reported in column (4) of Table 3. We find a large labor reallocation from farm work to off-farm work under each of the three climate change scenarios. The overall effect from GDDs and HDDs ranges from 8.89% to 35.90% across the scenarios. The labor reallocation effects of GDDs and HDDs are in the opposite direction, but the effect of HDDs is relatively small (even under the RCP8.5) and the overall effect is dominated by that of GDDs. Although we also find that climate change shifts farmers' time from leisure to off-farm work, the effect is small and statistically insignificant.

Finally, taking RCP4.5 as an example, we combine the projected end-of-the-century effects with the overall labor supply in rural China to roughly estimate the effect of climate change on the labor market. According to the National Bureau of Statistics of China, the rural labor force (working age rural residents) in 2012 was 258 million. Therefore, climate change will reduce the agricultural labor supply by 40.04 million people (i.e., 0.1552*258) and increase the off-farm labor supply by 44.09 million people (i.e., 0.1709*258).

5. Concluding remarks

Depending on a panel of field survey data from China, we find that climate change will significantly reallocate rural residents' time from farm work to off-farm work. The labor reallocation effect ranges from 8.89% to 35.90% across different climate change scenarios. The effect comes mainly from increases in the mean temperature instead of the increases in extreme heat. We also find significant differences in the effects of climate change between males and females.

The impact of climate change on time allocation has important economic and welfare implications. First, the outflow of labor from agriculture is likely to magnify the damage of climate change on total agricultural output (by reducing per hectare labor input). Second, the reallocation of time to off-farm work may increase urban unemployment and reduce off-farm wages. Third, the reduction of time allocated to leisure (mainly for males) represents an important negative impact of climate change on individual welfare, which has been generally ignored in the literature. Finally, the differing gender effects of climate change may lead to a significant change in labor structure and imbalanced welfare losses across gender. Further studies focusing on these topics may significantly enhance our understanding of the impact of climate change on economic performance and social welfare.

Finally, we would like to highlight some limitations to our work. First, our econometric estimates are based on data during 2009–2010 and may change depending on future technological progress, agricultural policies, and local demographic trends; therefore, the projected impacts are best interpreted as that conditional on current technology, policy, and demographic structure. Second, this partial equilibrium analysis makes an implicit assumption that the relative price of agricultural products to non-agricultural products is not affected by climate change; we will overestimate (underestimate) the labor reallocation effect if climate change increases (reduces) the relative price. Third, our analysis also implicitly assumes that wages outside the farm sector are constant; a decrease (increase) of non-farm wages would reduce (enhance) the incentive to leave farm jobs. Finally, our data limitation determines that we do not capture the effects of climate change on within-day reallocation of time between work and leisure.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2020.102376.

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