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Article

Too hot to work? Heat waves, household income, and labor adaptation in India

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SUMMARY

In a world of dynamic environmental changes, it is crucial to understand how the environment influences economic activities and performance for better policy making. However, studies on how developing countries are affected by and coping with climate change are still limited. Since India is a hot country with a large population highly vulnerable to extreme weather, this research aimed to investigate how average Indian households respond to climate change by examining the impact of rising temperatures on their economic activities and performance. We hypothesized that a rising temperature has negative relationships with Indian household income, agricultural income, household consumption, and farm labor inputs. Using temperature data and household data from 2012, we conducted both correlation analysis and regression analysis. Our results indicated significant negative relationships between heat waves and household income and consumption. In addition, the strongest negative correlation was between heat waves and agricultural income, suggesting that the agricultural sector was one of the production sectors most impacted by heat waves. Moreover, the correlation between heat waves and annual agricultural labor inputs was U-shaped, indicating potential adaptation when hot days occur more frequently. Robustness checks using different definitions of heat waves and transforming our data for better linearity gave similar results. This research suggested that to improve agricultural income during heat waves, policies should focus on enhancing agricultural productivity, rather than labor inputs.

INTRODUCTION

Research has documented that heat waves can negatively impact worker productivity and income, as high temperatures have been shown to decrease human physical and cognitive capabilities (1, 2). Studying the effect of hot weather on income and labor participation is crucial for understanding how short-term environmental conditions and long-term climatic trends influence economic performance and social welfare, which can in turn provide guidance on policy making. The relationship between weather and economic performance also provides valuable insights into the adaptation, resilience, and sustainability of any society in the face of global climate change (3). Lots of research has been conducted to investigate the influence of temperature on a variety of aspects of economic activities, including household income, production and productivity, migration, and adaptation (4–10). However, understandings on how high temperatures impact economic performance and adaptation in developing countries including India are still limited.

India is a prime case for examining the correlation between weather and economic performance. India has a tropical climate and is generally considered a hot country (11). Most Indian counties, especially those in the central and northern regions, experience extremely hot summers, with temperatures often reaching above 40°C during the peak summer months (11). Furthermore, the Indian economy significantly relies on weather-dependent sectors like agriculture, and India has a large population that is highly vulnerable to extreme weather events (12–14). Our research examined the impact of heat waves on household income, agricultural labor inputs, and consumption in India, aiming to gain insights into the relationships between temperature and economic performance. In this work, we defined labor inputs as the amount of labor time contributed to the production of goods and services and consumption as the household expenditure on non-investment goods and services. In addition, household income included household agricultural income and non-agricultural income. The relationship between income/productivity and a rising local temperature in general is bell-shaped when starting from a relatively low average temperature, with a strong positive correlation between household wealth and higher temperatures in cold countries, and a strong negative correlation between household wealth and higher temperatures in hot countries (15). Note that an increasing income in response to temperature corresponds to a positive relationship whereas a decreasing income in response to temperature corresponds to a negative correlation. Thus, the relationship between household income and local temperature was expected to be negative in India, as it is a hot country with an average temperature of approximately 25°C from 1901 to 2024 (11). Moreover, a rising local temperature was expected to have a negative correlation to labor inputs, unless people show strong adaptation to climate change. On the other hand, it was not immediately clear whether the correlation between higher local temperatures and household consumption is positive or negative. While hotter days may lower household income and thereby force people to consume less, they may also increase the consumption of necessities like water and electricity as people try to adapt to the hot weather. We posited that the first effect of heat waves is stronger than the second effect, which meant that the lowered consumption due to lowered income dominated the increased consumption on necessities. As a result, there would be a negative correlation between higher local temperatures and consumption. Therefore, we hypothesized that a rising local temperature negatively affects Indian household income, agricultural income, consumption,

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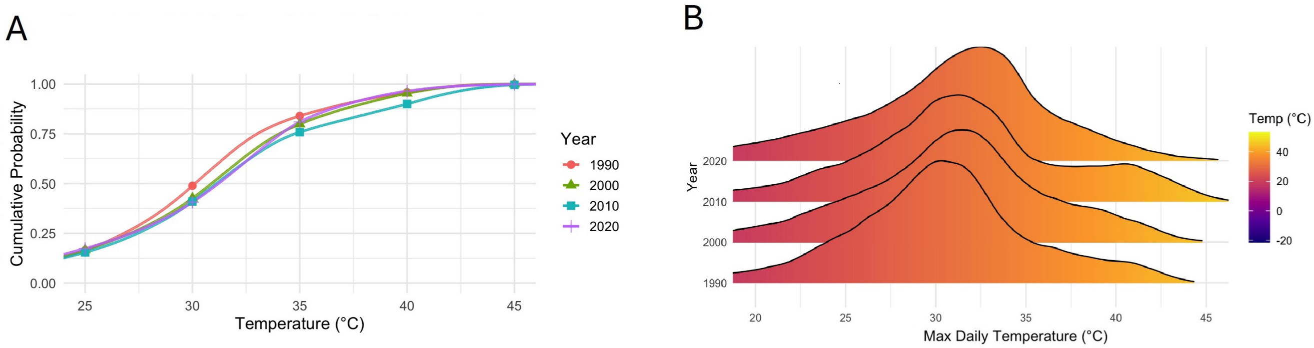

Figure 1. Maximum daily temperatures in India in the years 1990, 2000, 2010, 2020. (A) The cumulative distribution plot of maximum daily temperatures with range zoomed to 25-45°C.The value 0.5 of cumulative probability on y-axis corresponds to the annual median maximum daily temperature on x-axis. (B) The density ridge plot of maximum daily temperatures with range zoomed to 20-45°C. The peak point of each curve shows the most frequent maximum daily temperature of the corresponding year.

and farm labor inputs.

In this work, we compared the Indian local temperature in 2012 with a fifty-year average local temperature and counted the excessively hot days (i.e., days with temperature exceeding the 95th percentile of the temperature distribution). We used the count of excessively hot days as the proxy of heat waves since they reflected the same trend in the temperature change. We used the year 2012 because it was the most recent year of household data we were able to obtain. We then studied how the occurrences of local heat waves impacted Indian household economic performance. Our results indicated that local heat waves had a significant negative correlation with Indian household income per capita, agricultural income, consumption per capita, and agricultural labor inputs. In addition, we found that the negative correlation was strongest with agricultural income, suggesting that the agricultural sector was one of the most impacted production sectors by heat waves. Moreover, a significant U-shaped relationship existed between heat waves and annual farm days/hours, suggesting a potential adaptation in labor inputs when hot days become more frequent. Therefore, our results not only highlighted the negative impacts of heat waves on Indian household welfare but also provided policy guidance regarding how government might help improve agricultural productivity under higher temperatures.

RESULTS

Our aim was to examine how higher temperatures affect Indian household economic activities and performance. We provided descriptive statistics of our household variables and temperature measurements. After that, we conducted both correlation analysis and regression analysis to investigate the correlation between high temperatures and household variables.

Summary Statistics

India was experiencing an increasing average temperature over the past thirty years (**Figure 1**). The annual median maximum daily temperature was 30.1°C in 1990, 30.9°C in 2000, 31.1°C in 2010, and 31.2°C in 2020 (**Figure 1A**). The most frequently occurring maximum daily temperature was 30.3°C in 1990, 31.4°C in 2000, 31.2°C in 2010, and 32.5°C in 2020 (**Figure 1B**).

We used boxplots to provide descriptive statistics of all the numeric variables (**Figure 2**). There are five household economic variables: household income per capita (INCOMEPC); household consumption per capita (COPC); household income from agriculture minus expenses (INCAG); number of annual days spent on farm work (Farm Days); number of annual hours spent on farm work (Farm Hours). The first three variables have mean values of 26,163.18, 24,242.24, 29,599.43 and median values of 15,170, 17,750.17, 0 respectively. Farm Days have a mean value of 114 days and a median value of 90 days. Farm Hours have a mean value of 566 hours and a median value of 360 hours (**Figure 2A**). We measured the number of days with excessive heat as a proxy of heat waves. There are four different measurements of the number of excessively hot days: p95outlier, p99outlier, twoSDoutlier, and IQRoutlier. Here p95outlier was used in our baseline analysis and the other three measurements were used for robustness checks on our results. Among them, p95outlier is the least restrictive, with a mean value of 28 days and a median value of 29 days. IQR outlier is the most restrictive, with a mean value of 2.65 days and a median value of 2.26 days. The mean and median values of p99outlier and twoSDoutlier are (7.16, 5.32) and (10.11, 6.46), respectively (**Figure 2B**).

Correlation Results

We analyzed the relationship between temperature and household economic variables using Pearson correlation and Spearman correlation. We found weak linear relationship

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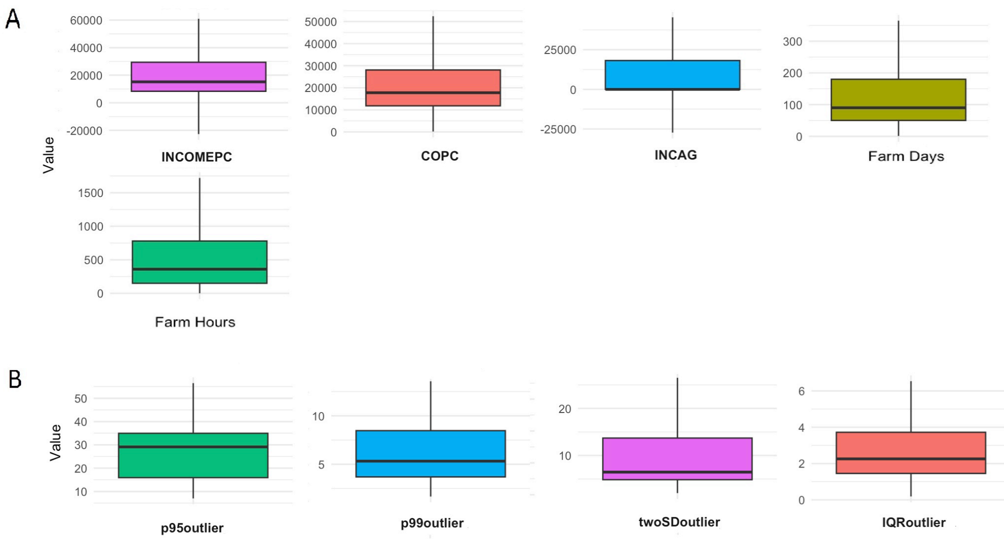

Figure 2. Boxplots of numerical variables. (A) Boxplots of household economic variables: household income per capita (INCOMEPC); consumption per capita (COPC); agricultural income (INCAG); annual farm days (Farm Days); annual farm hours (Farm Hours). Axes are automatically cropped to the 1.5*IQR whiskers. Number of observations and standard deviation from the mean are (20,3520, 45,529.08) for INCOMEPC, (203,430, 26,056.34) for COPC, (203,520, 134,646.94) for INCAG, (46,193, 84.76) for Farm Days, (46,168, 591.04) for Farm Hours. (B) Boxplots of heatwave measurements: p95outlier, p99outlier, twoSDoutlier, and IQRoutlier. Axes are automatically cropped to the 1.5*IQR whiskers. Number of observations for each measurement is 203,521; standard deviation from the mean is 15.02, 5.06, 6.66, 1.67 respectively.

between each of our five household economic variables and heat waves based on Pearson correlation results (*r = -0.05, -0.02, -0.07, 0.02, -0.08* for correlation between heat waves and income per capita, consumption per capita, agricultural income, annual farm hours, and annual farm days, respectively*)*.

A basic assumption of Pearson correlation is that the data are normally distributed. However, Normal Quantile-Quantile (Q-Q) plots showed that our data violated this assumption (**Figure 3**). Among our household variables, consumption per capita, annual farm hours, and annual farm days were all skewed to both the left and right (**Figure 3A, B, C**), while per capita income and agricultural income were highly right-skewed (**Figure 3D, E**). Since normality was violated, we employed Spearman's rank correlation to gain further insights into these relationships. The signs of Spearman coefficients were the same as of Pearson coefficients. The coefficients indicated that monotonicity was generally weak among all

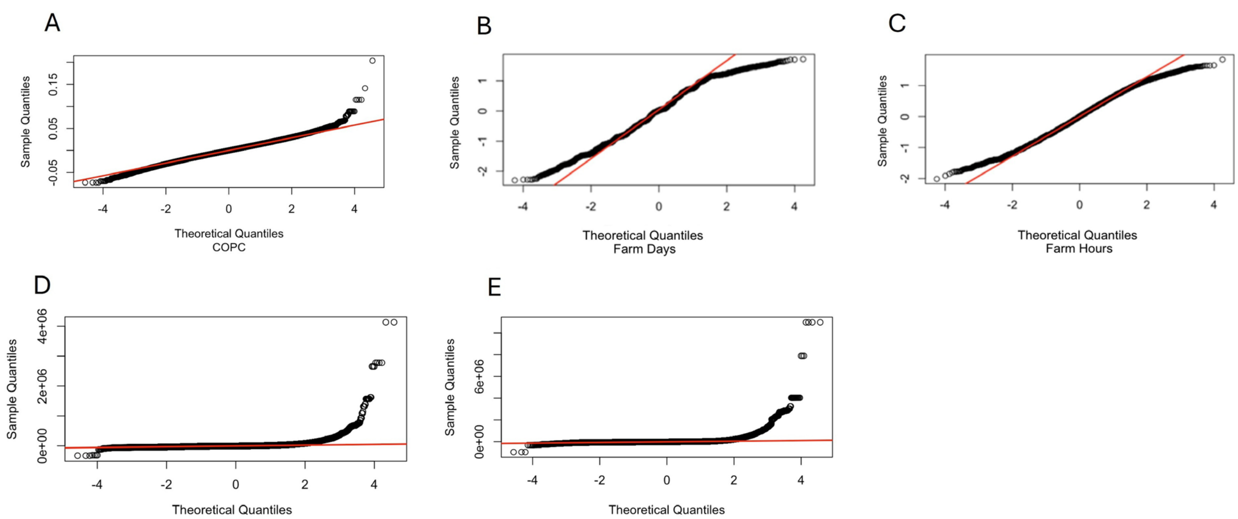

Figure 3. Normal quantile-quantile (Q-Q) plots of household economic variables. The Q-Q plot for (A) household consumption per capita (COPC), (B) annual farm days, (C) annual farm hours, (D) income per capita (INCOMEPC), and (E) agricultural income (INCAG). Data are plotted as black open circles, while the red line indicates perfect normality. In each panel, data points deviate from the red line, indicating that the data is not normally distributed.

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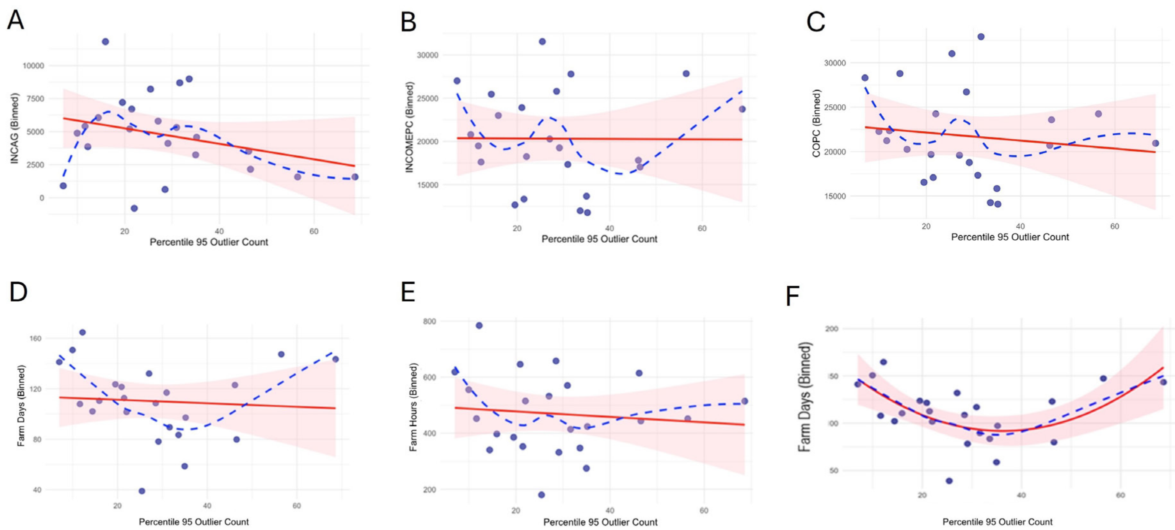

Figure 4. Scatter plot diagrams on correlations between heat waves and household variables. The linear relationship between heat waves (measured by the count of excessively hot days) and (A) household agricultural income (INCAG), (B) income per capita (INCOMPEC), (C) consumption per capita (COPC), (D) farm days, and (E) farm hours, (F) Quadratic fit of the relationship between heat waves and annual farm days. The x-axis is the count of excessively hot days by summing the number of days with temperature exceeding the 95th percentile of the temperature distribution for a given state in 2012. The red line shows the best fit under a (A–E) linear or (F) quadratic assumption. (A–F) The red shaded area shows the trendline's 95% confidence interval, and the blue dashed line is the Locally Estimated Scatterplot Smoothing (LOESS), which fits a smooth curve to the scatter plot without a structural assumption.

Variables	INCOMEPC		INCAG	
	Coef	SD	Coef	SD
p95outlier	-85.898***	(7.173)	-607.866***	(18.315)
p95outlier^2				
Urban dummy	10906.248***	(232.964)	-40875.921***	(596.276)
College dummy	28599.038***	(387.104)	31077.035***	(1168.299)
Bradmins dummy	5711.682***	(531.794)	-6589.561***	(1233.031)
Sample size	203035		203035	

Variables	COPC		Farm Days	
	Coef	SD	Coef	SD
p95outlier	-37.364***	(3.695)	-2.867***	(0.140)
p95outlier^2			0.041***	(0.002)
Urban dummy	7762.222***	(120.201)	-18.217***	(1.891)
College dummy	14762.582***	(148.175)	10.428***	(1.329)
Bradmins dummy	5361.963***	(255.753)	2.699	(1.972)
Sample size	202961		46143	

Variables	Farm Hours	
	Coef	SD
p95outlier	-9.818***	(1.032)
p95outlier^2	0.207***	(0.017)
Urban dummy	-131.723***	(12.474)
College dummy	38.824***	(9.286)
Bradmins dummy	-64.016***	(12.268)
Sample size	46118	

Table 1. Impacts of heat waves using Ordinary least squares (OLS). Heat waves have negative and significant correlations with all household variables, and the negative impact on agricultural income shows the largest scale. While heat waves initially show a negative correlation with annual farm days and hours, the U-shape in their correlations is significant. Here p95outlier is a heat wave measurement. Urban dummy with value 1 indicates that the household is located in urban areas; College dummy with value 1 indicates that the highest education received within a household is bachelor's or above; Brahmins dummy with value 1 indicates that the household belongs to the highest Indian caste. Coef = correlation coefficient. SD = robust standard deviations, which are shown in parentheses. (*** p<0.01, ** p<0.05, * p<0.10).

five relationships. Agricultural income (*r=-0.11*), income per capita *(r=-0.11)*, and consumption per capita *(r=-0.11)* exhibited stronger monotonicity with heat waves relative to annual farm hours (*r=0.01*) and annual farm days (*r=-0.07*). Next, to better visualize the correlations between heat waves and household variables, we plotted each relationship as a scatter plot. Out of these household variables, agricultural income has a clear negative relationship with heat waves, illustrated by the downward-sloping red line (**Figure 4A**). Consumption per capita also falls as the occurrence of heat waves increases. However, the correlation between income per capita and heat waves is unclear and non-monotonic (**Figure 4B, C**). The linear trend appears to be negative with annual farm hours/days, while LOESS shows a U-shape relationship between heat waves and these two variables (**Figure 4D, E**). As the U-shape is clear between heat waves and annual farm days, we also conducted a quadratic fit to assess their relationship (**Figure 4F**). We found a quadratic relationship between heat waves and annual farm days, suggesting that annual farm days initially fall as heat waves occur but eventually bounce back when heat waves occur more frequently (**Figure 4F**).

Regression Results

We then used the ordinary least squares (OLS) regression to further explore the relationships between heat waves and household economic variables. OLS regression requires several preconditions. Our sample size of 203,521 is less than 10% of the total population of India, ensuring independence of observations in the sense that each data point is unrelated to others. To address the potential issue of heteroskedastic regression errors, we applied HC3 robust standard errors to our OLS regression models. HC3 is one type of modification

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of the heteroskedasticity-consistent (HC) standard errors, which does not change the regression coefficients but corrects the t-test statistics of the regression coefficients for heteroskedasticity.

In the regression results, heat waves have negative and significant correlations with all five variables: income per capita, agricultural income, consumption per capita, annual farm days, and annual farm hours. Among them, the negative impact on agricultural income shows the largest scale, with one more hot day related to a drop of more than 600 Rupees. On the other hand, one more hot day is related to a drop of 86 Rupees in income per capita and a drop of 37 Rupees in consumption per capita (**Table 1**). While heat waves initially show a negative correlation with annual farm days and hours, the U-shape in their correlations is significant, verified by the positive and significant coefficient of the squared heat waves (**Table 1**).

Across the household features, being located in urban areas, getting at least a college degree, and belonging to the highest caste are all positively correlated with income per capita and consumption per capita. Living in urban locations and belonging to the highest caste are negatively correlated with agricultural income and annual farm hours, possibly because these groups of people take fewer agricultural jobs. On the other hand, obtaining at least a college degree is positively correlated with agricultural income and annual farm days/hours (**Table 1**). One potential explanation is that people with higher education tend to get full-time jobs when they choose to work in the agricultural sector.

We utilized multiple robust checks of the above regression results. One examination was to use different measurements for heat waves, including p99outlier and twoSDoutlier. The results asserted that the relationship between heat waves and our variables remains the same; only the coefficients of heat waves get bigger in absolute values, showing a larger scale of response among household variables to the occurrence of severe heat events. Since IQRoutlier measures the occurrence of extremely hot days, it exhibits the strongest negative correlation with the household economic variables (**Table 2**).

Since the Pearson test indicated a rather weak linear relationship between heat waves and our household variables, we conducted a log-log transformation, a frequently used method to improve linearity and handle skewed data, on some variables as another robustness check. Because data values of consumption per capita and annual farm days/hours are all positive, log-log transformations were conducted on these data sets and the heat wave counts. The OLS results using transformed data indicated that the negative relationships are preserved between heat waves and consumption per capita (regression coefficient is -0.110 with robust standard deviation 0.002) as well as annual farm days (regression coefficient is -0.123 with robust standard deviation 0.009).

Variables	INCOMEPC		INCAG	
	Coef	SD	Coef	SD
IQRoutlier	-1465.035***	(58.997)	-4685.460***	(147.083)
IQRoutlier^2				
Urban dummy	11057.576***	(231.028)	-41192.547***	(600.279)
College dummy	28437.793***	(386.174)	30284.808***	(1171.860)
Bradmins dummy	5430.264***	(530.597)	-5228.023***	(1238.548)
Sample size	203035		203035	

Variables	COPC		Farm Days	
	Coef	SD	Coef	SD
IQRoutlier	-423.023***	(38.548)	-10.808***	(0.990)
IQRoutlier^2			0.875***	(0.147)
Urban dummy	7775.872***	(126.660)	-16.786***	(1.915)
College dummy	14705.711***	(126.660)	10.792***	(1.337)
Bradmins dummy	5365.920***	(378.714)	1.558	(1.973)
Sample size	202961		46143	

Variables	Farm Hours	
	Coef	SD
IQRoutlier	-75.334***	(6.941)
IQRoutlier^2	10.322***	(1.031)
Urban dummy	-121.522***	(12.611)
College dummy	44.700***	(9.314)
Bradmins dummy	-88.812***	(12.289)
Sample size	46118	

Table 2. Impacts of extremely hot days using OLS. The correlations between heat waves and household variables are stronger, showing a larger scale of response among household variables to extremely hot days. IQRoutlier is a heat wave measurement. Coef = correlation coefficient. SD = robust standard deviations, which are shown in parentheses. (*** $p<0.01$, ** $p<0.05$, * $p<0.10$).

DISCUSSION

Our correlation and regression results asserted negative impacts from high temperatures on multiple Indian household economic variables. Moreover, household agricultural labor inputs exhibit a potential adaptation when excessively hot days were more frequent. Our results provided some policy guidance about improving agricultural productivity.

We expected that heat waves and Indian household income would have a negative relationship, which was confirmed by our correlation and regression results. In addition, the negative effect of heat waves is more severe on agricultural income, suggesting that the agricultural sector is one of the production sectors most impacted by heat waves. While heat waves may either increase or decrease household consumption, our results indicated a negative correlation between heat waves and consumption.

Our Pearson and Spearman correlation coefficients showed a negative relationship between heat waves and annual farm days, yet a very weak positive relationship between heat waves and annual farm hours. It is not clear whether hot days are negatively related to agricultural labor inputs. However, the significant U-shape in the correlation between heat waves and annual farm hours from our regression results indicated that the weak positive Pearson and Spearman coefficients could reflect the aggregate effect from a U-shaped relationship. Days/hours spent at farm work initially drop but eventually bounce back as the number of hot days continues to increase, showing a potential adaptation when people realize that higher-than-usual temperature becomes the norm, and they need to continue with farm work to make up for the loss from high temperature. Therefore, policies may focus more on improving agricultural production conditions and productivity, as the agricultural sector is fragile to heat waves and its income is impacted mainly by lowered productivity rather than lowered labor inputs on hot days.

When log-log transformation was conducted for better linearity, our major results continued to hold. We noted, however, that the correlation between annual farm hours and

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heat waves became positive in our regression results. While this appeared to indicate a very strong adaptation in farm hours to more frequent heat waves, we recognized that the result could reflect data overfitting due to the limited number of observations on the high frequency of hot days in our data set.

Our results regarding agricultural adaptation to higher temperatures correlated with other research work. In one study, Indian farmers were found to have adopted a wide range of adaptation measures in response to higher temperatures, including substantial changes in land use, resource and labor allocations, occupational pattern, and cropping systems (13). Our policy suggestions were also supported by the literature, which recommended large-scale investments in Indian agriculture to improve farmers' capacity including their perception of climate change and adoption of adaptation measures (13).

Our findings were consistent with previous literature on how hot days impact productivity and income (12, 16–18). Using microdata from selected industrial firms in India, reduced worker productivity and increased absenteeism on hot days were estimated and annual plant output was found to fall by approximately 2% per degree Celsius (12). Based on survey data from China, hot days were found to be negatively correlated not only with real income but also with perceived income (16). Using data from 14 European countries, it was shown that heat waves significantly reduce individual income (17). With the occupational heat stress index WBGT to quantitatively estimate the impacts of climate change on work activities in countries and local communities, it was found that areas experiencing severe heat stress would expand, resulting in more substantial losses in work capacity and labor productivity (18). Our study therefore added to the growing body of literature indicating that increasing global temperatures negatively impact the labor force and local economies.

Our results also reinforced the literature message that the agricultural sector, due to its greater temperature exposure, is more fragile to heat waves. A systematical review of the literature on farmers' perception of and adaptation to the rapidly changing climatic conditions in India found that the majority of the Indian farmers had perceived a rising temperature and decreased rainfall and concluded that climate change is adversely affecting the Indian agricultural sector (13). The relationship between heat stress and household wealth across 52 countries was examined. Besides a strong negative correlation between household wealth and higher temperatures in many hot countries, it was found that people in poverty were more likely to work in occupations with greater temperature exposure and, therefore, were more impacted by rising temperatures (15).

Literature had mixed messages on how heat waves affected consumption. On the one hand, hot weather may increase consumption due to the higher need for necessities, including water, medicine, and utilities. For example, it was shown that in two Indian cities, during heatwave days, low-income urban workers who were exposed to the heat worked fewer hours and spent more on routine purchases such as food than during days of normal weather (1). In addition, multiple groups have studied the influence of heat waves on health, mortality, health care services, and adaptation (i.e., adjustment to environmental conditions); their findings indicated worsened health situation and increased demand on health care due to hot days (2, 19, 20). On the other hand, heat waves may also decrease consumption through lowered income (21). The reason is that excessively hot weather may force people to reduce labor inputs, which lowers income and thereby lowers consumption. Our regression results indicated that the second impact from heat waves on consumption was dominant, resulting in a negative and significant relationship between heat waves and consumption per capita.

Literature indicated different adaptations to extreme temperatures across countries and populations at different income levels. For example, one study investigated how heat vulnerability affects household income and adaptation in Germany. The results indicated that while heat exposure levels were comparable between income groups, low-income households were more heat-sensitive and had lower adaptation to heat stress (22). Another work showed that a global temperature change of 2.7 degrees Celsius could impose very different heat impact on work across different countries (18). Our work complemented previous literature by focusing on the Indian agricultural sector and investigating how farm workers adapted when hot days became more frequent. Our findings showed that the agricultural sector was more sensitive to heat and agricultural labor inputs exhibited a significant adaptation to heat waves.

Our work hence contributed to the literature studying the impacts of heat waves on income, consumption, and labor adaptation. Our results suggested that policies may focus more on improving agricultural production conditions and productivity, as the agricultural sector is fragile to heat waves and its income is impacted mainly by lowered productivity on hot days.

While the household dataset used in this paper was extensive in the number of Indian states included, it only covered one year of information. Therefore, there is the limitation of utilizing our results as it is not clear if the pattern is currently the same. In addition, we cannot directly generalize our results and cannot examine the impacts of heat waves across multiple years to gain a clear view of the trend. Instead, we looked at the regional impacts of heat waves on economic activities across various states, with several variables of household features controlled. Moreover, we did not have data on agricultural outputs like crop yield, therefore we cannot further examine how agricultural productivity is impacted by heat waves, or if there are other confounding factors affecting agricultural income. A more comprehensive data set with data across multiple years for household income, consumption, labor inputs, agricultural outputs, and other household features will allow for a more precise and quantitative estimation of the impacts of heat waves on local economies. Our work was also limited by our measuring heat waves by counting their occurrences, and our lack of measurements on temperature-related trends including rainfall and humidity. In future work, measuring heat waves by not only their occurrence but also their magnitude and duration, and including measurements on rainfall or humidity, will enrich our insights regarding how heat waves with different severity levels tend to impact economic activities and social welfare.

MATERIAL AND METHODS

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Data Acquisition

The temperature data was obtained from ERA5, an open source of global climate and weather data with the highest daily temperature data available from 1940 onwards (23). The daily temperature of 2012 of each district was taken. Based on each district, the monthly average temperature distribution over 1970–2020 was calculated and various standards were used to identify the number of "hot" days for each month in 2012. Note that there were four different measurements of the number of excessively hot days: p95outlier, p99outlier, twoSDoutlier, and IQRoutlier. Among these measurements, p95outlier was used as the measurement for heat waves in our baseline analysis. Here p95outlier was the count of the number of days with temperature exceeding the 95th percentile of the temperature distribution. The monthly hot days were summed up to have the yearly hot days for each district. The count of heat waves was at the state level, given by the average number of yearly hot days across districts located within each state. In addition, IQR outliers were calculated at the state level to create a measurement for extremely hot days in each state, as IQR is a common statistical tool to identify outliers. Any day in a given month with the highest temperature exceeding the upper threshold (Q3 + 1.5*IQR) was considered an outlier. The robustness of our major results was checked and verified by using the other definitions of hot days, p99outlier, twoSDoutliner, and IQR outliers. Here p99outlier counted the number of days with temperature exceeding the 99th percentile; and twoSDoutlier counted the number of days with temperature at least two standard deviations above the mean monthly temperature.

Our household data came from the India Human Development Survey-II (IHDS-II), 2011–2012, which was a nationally representative, multi-topic panel survey over 33 states, 384 districts, 1,420 villages, and 1,042 urban neighborhoods across India, with 204,569 total observations (24). IHDS-II covered all Indian states and union territories except for the distant Indian island groups Andaman/Nicobar and Lakshadweep. Over half of IHDS-II households had some farm income, and about 11% reported negative farm income due to crop failures and high expenses. Out of the total observations, 46,292 observations (22.6%) reported engaging in farm work (24). Based on the household data, several control variables were created: Brahmins, Urban, and College, all were dichotomous variables valued at either 1 or 0. India has a complex caste system encompassing thousands of castes and sub-castes, and Brahmins are the highest caste category (25). As the caste affects Indian households' access to resources including education and jobs, Brahmins was used as one control variable, with value 1 indicating that the household belongs to the highest Indian caste, and value 0 otherwise. Urban with value 1 indicated that the household was located in urban areas; and College with value 1 indicated that the highest education received within a household was a bachelor's degree or above. In our data, there were 10,253 Brahmins out of 204,114 valid cases, accounting for about 5% of the total. The variable Urban grouped together metro urban and other urban locations as identified by the 2011 Indian census. There were 69,524 urban observations, accounting for 34% of the total, and 66% observations were located in rural areas. In the data, 37,596 out of 204,537 observations had college or higher education within the household, about 18.4% of the total observations.

Once the temperature data were merged with household data according to each household's state ID, there were 203,521 valid observations. The drop of 1,048 observations was because the temperature data does not include the Indian cities Chandigarh and Pondicherry or the Indian union territories Daman and Diu. Among our household economic variables, INCOMEPC, COPC, and INCAG were all measured in Rupees. Using the merged data set, descriptive statistics of all the numeric variables were provided with missing values excluded. RStudio was the software used in the research on all summary statistics, Pearson and Spearman correlation tests, and OLS regression.

Data Analysis

Correlation and regression analysis were used for studying the relationship between heat waves and household economic performance. All our statistical and regression analysis used the merged data set.

Pearson correlation tests were performed to determine the strength of correlation between each household economic variable (household income per capita, agricultural income, consumption per capita, annual farm days, and annual farm hours) and p95outlier, the proxy of heat waves. Normal Quantile-Quantile (Q-Q) plots were used to check if our data is normally distributed. A Normal Q-Q plot is a parametric curve that plots the data's normally distributed quantiles against the observed data distribution; if the observed distribution follows normality, the points of the curve will fall along the identity line. Deviations from this identity line suggest that the data is not normally distributed. Spearman's rank correlation evaluates how well a monotonic process shows the affinity between two variables. In our Spearman correlation test, the affinity between each household economic variable and the heat wave count p95outlier was evaluated.

Ordinary least squares (OLS) is a basic linear regression formula that models how a dependent variable y corresponds to independent variables x (26). In our OLS regressions, the dependent variable was each household economic variable. The independent variables were the heat wave count p85houtlier, and the control variables (Brahmins, Urban, College). In addition, as both annual farm days and annual farm hours were U-shaped in heat waves in the scatter plots, the quadratic term of heat waves was also controlled for in the regressions of these two variables to examine the significance of the U-shape.

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