Is it Too Hot to Work? Evidence from Peru

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Abstract

Will rising temperatures from climate change affect labor markets? This paper examines the impact of temperature on hours worked, using panel data from Peru covering the period 2007 to 2015. We combine information on hours worked from household surveys with weather reanalysis data. Our findings show that high temperatures reduce hours worked, with the effect concentrated in informal jobs rather than in weather-exposed industries. These results suggest that labor market segmentation may shape how climate change affects labor outcomes in developing countries.

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1 Introduction

The ILO (2019) projects that global warming will reduce hours worked by 2.2%, equivalent to the loss of 80 million full-time jobs globally by 2030. However, empirical evidence on the effects of rising temperatures on time use remains limited, especially in developing countries (Dell et al., 2014; Burke et al., 2016; Jack, 2017; Connolly, 2018). Understanding this labor-temperature relationship is particularly important for developing countries, as they concentrate 80% of the world's labor force (Behrman, 1999), they are located in tropical areas where temperature variation due to climate change is relatively more pronounced (Aragón et al., 2021), they are expected to face higher associated costs of climate change (Dell et al., 2014; Jessoe et al., 2016), and they have a high incidence of asset-poor households with limited access to adaptation strategies or the ability to engage in avoidance behavior (Jessoe et al., 2016).

This paper examines the impact of temperature changes on hours worked using data from Peru, emphasizing the importance of labor market segmentation in assessing the effects of climate change on labor outcomes. We contribute new evidence on how temperature shocks influence work time in a middle-income country and explore intertemporal labor substitution as a potential adaptation mechanism. Peru offers an ideal setting for this analysis, given its high vulnerability to climate change and pronounced labor market segmentation—characteristics it shares with many other low- and middle-income countries.

This paper combines longitudinal microdata on workers from household surveys with meteorological reanalysis data for Peru from 2007 to 2015. We exploit quasi-random year-to-year variation in temperature within residential localities to estimate whether individuals work more or fewer hours per week in warmer years. While this empirical approach helps minimize concerns about omitted variable bias (Deschenes and Greenstone, 2007), we also control for rainfall, relative humidity, and daylight hours—factors that are correlated with temperature and may independently influence working hours.

The empirical analysis yields three main findings. First, we find that high temperatures have a negative effect on overall working hours. On average, individuals reduce their weekly work time by 0.63 hours (approximately 40 minutes) for each additional day with temperatures exceeding 27°C, relative to days within the human thermal comfort zone (i.e., between 18-21°C), under average relative humidity conditions of approximately 76%. This effect is more pronounced among informal workers, for whom the reduction reaches up to 52 minutes. Although a decrease of 0.63 hours represents a relatively modest decrease of 1.45% in the average number of hours worked per week, the cumulative impact across millions of workers leads to significant aggregate economic losses, amounting to approximately 0.6% of the national GDP.

Second, the negative effect of high temperatures on work time is driven by informal employment. While prior studies in developed countries have shown that high temperatures tend to reduce hours worked in sectors with primarily outdoor jobs, our findings suggest that in the context of a highly segmented labor market—such as that of many developing countries—the type of industry becomes less relevant. In such settings, informal workers experience reductions in working hours due to high temperatures regardless of whether their jobs are performed indoors or outdoors.

Third, we find no evidence of intertemporal labor substitution as a mechanism for adapting to temperature changes. In response to high temperatures, workers do not appear to shift their work hours across weeks. This suggests that the reduction in hours worked is not merely temporary, but may instead reflect a persistent effect of heat on labor supply.

This study contributes to the growing literature on the impacts of climate change on labor market outcomes. Prior research has examined the effects of weather shocks on work time (Connolly, 2008; Zivin and Neidell, 2014; Kruger and Neugart, 2018; Schwarz, 2018; Garg et al., 2020; Gray et al., 2023); ability to work (Heyes and Saberian, 2022); wages (Schwarz, 2018); earnings (Das and Somanathan, 2024); productivity (Dell et al., 2014; LoPalo, 2020; Somanathan et al., 2021); absenteeism (Somanathan et al., 2021); and labor reallocation (Jessoe et al., 2016; Colmer, 2020). However, little attention has been paid to the role of labor market segmentation—a pervasive feature of labor markets in developing countries—in shaping the future impacts of climate change on labor outcomes. The study most closely related to ours is Gray et al. (2023), which uses a linear probability model to examine the effects of droughts and temperature on employment in South Africa. They find no statistically significant effects of temperature on overall, formal, or informal employment. In contrast, we focus on the intensive margin of labor supply and study a context—Peru—with greater variation in weather conditions. Additionally, this paper contributes to the literature on weather and intertemporal labor supply, which has largely focused on high-income countries such as the United States and Germany (Connolly, 2008; Zivin and Neidell, 2014; Kruger and Neugart, 2018) with China as a notable exception (Garg et al., 2020).

The remainder of the paper is organized as follows. Section 2 provides background context. Section 3 describes the data used to measure weather conditions and work hours. Section 4 outlines the empirical strategy. Section 5 presents the main results, followed by a discussion of informal employment in Section 6. Section 7 concludes.

2 Background

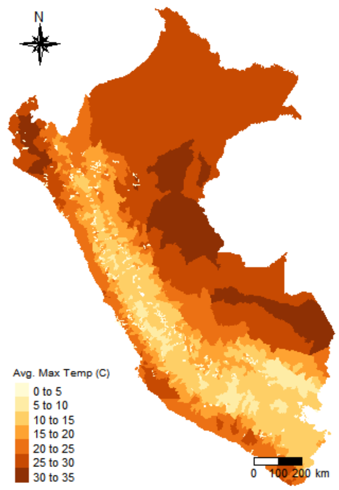
Peru is geographically divided into three main regions—the coast, the highlands, and the jungle—and is considered highly vulnerable to climate change. The country features low-lying coastal zones; arid and semi-arid areas; regions prone to flooding, drought, and desertification; fragile mountain ecosystems; disaster-prone zones; areas affected by high levels of urban air pollution; and economies that rely heavily on income from fossil fuel production and use (MINAM, 2015). These characteristics correspond to seven of the nine criteria established by the United Nations for classifying a country as particularly vulnerable to climate change. Additionally, Peru exhibits significant climatic diversity, encompassing over 70% of the world's climate types (MINAM, 2014). The vast majority of this climatic diversity is concentrated in the coastal and highland regions of the country (SENAMHI, 2020). Figure 1 illustrates the distribution of temperatures across Peru.

3 Data

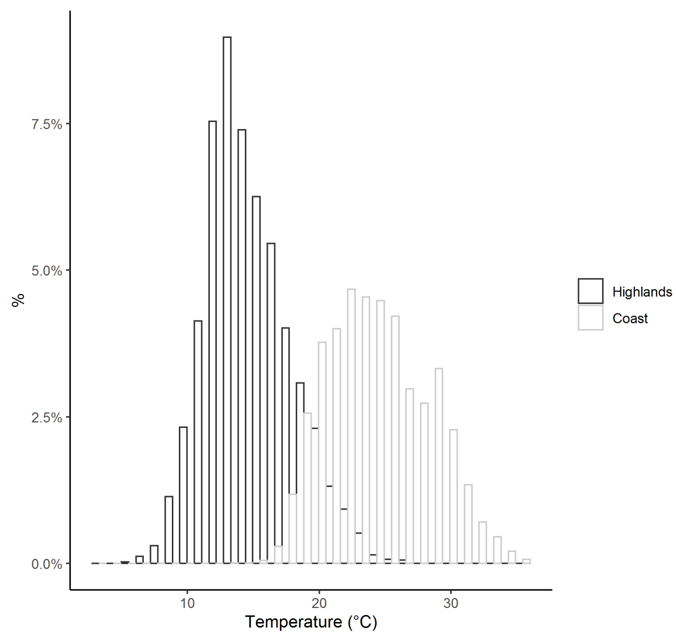
This paper examines the relationship between temperature changes and work-time allocation. We combine worker-level data from household surveys with meteorological reanalysis data for Peru. The unit of observation is the worker-year, and weather conditions (temperature, relative humidity, and rainfall) are assigned to each household by overlaying meteorological data with the household's geographic coordinates (longitude and latitude). The analysis is restricted to workers in the coastal and highland regions—which together represent over 85% of the country's labor market—due to limitations in satellite data accuracy for the jungle region (Aragón et al., 2021). The final sample includes 113,392 worker-year observations spanning the period from 2007 to 2015. Summary statistics for the main variables are presented in Table A1 of the Appendix.

Labor Data We use two panel datasets from the Peruvian Living Standards Survey (ENAHO), one covering the period 2007-2011 and the other covering the period 2011–2015. This nationally representative survey collects data year-round at both the household and individual levels. Each worker in the panel is interviewed during the same calendar month across different years, which helps control for seasonality in weather. The households that participated in the 2007-2011 panel differ from those in the 2011–2015 panel, with the exception of a subset of households that were interviewed in 2011 and appear in both panels.

Figure 1: Temperature distribution in Peru.



(a) Avg. Max Temperature (°C) in 2015 (district level)



(b) Coast vs. Highlands

Note: The figure illustrates the temperature distribution across Peru using maximum temperature data from ERA5. Panel (a) displays the average district-level temperature for the year 2015. Panel (b) presents the distribution of temperatures in the coastal and highland regions over the 2007–2015 period.

Within each panel period, households can be observed for two to five years, depending on their participation. It is important to note that households present in both panels may have data spanning up to six years (see the number of years households and individuals are observed in our sample in Table A7 in the Appendix). Households were included in the main analysis if they were observed at least twice in either the 2007–2011 or the 2011–2015 panels. These may consist of households appearing exclusively in the first panel, exclusively in the second, or in both. For robustness, I additionally employ the repeated cross-section sample, which includes all households regardless of the number of appearances, thereby incorporating households observed only once.

This survey includes the interview date and provides geographic coordinates (longitude and latitude) for each participating household. Less than 0.03% of the sample was excluded due to missing geographic information. While we observe the household location, the precise coordinates of the workplace are not available. However, according to the 2017 National Census, 67% of the national labor force works within their residential district, which helps mitigate concerns about the absence of precise workplace coordinates.

We use the employment module to calculate total daily and weekly working hours for each individual, regardless of the number of jobs held. Notably, 26% of the sample reports having a secondary job, while only 1% reported zero hours worked. In this module, working-age individuals provide detailed information on their time allocation to work for each day of the *reference week*—defined as the week immediately preceding the interview date—along with other socio-economic characteristics.

Temperature and (Relative) Humidity. We use data from ERA5, produced by the European Centre for Medium-Range Weather Forecasts (Muñoz Sabater, 2019) to calculate average, maximum, and minimum daily temperatures and daily relative humidity for each household location. ERA5 offers hourly observations of surface air temperature and humidity on a 0.25×0.25 degree latitude-longitude grid, providing significantly higher spatial and temporal resolution than its predecessor, the widely used ERA-Interim archive (Auffhammer et al., 2013). When temperature data are missing for a specific day and household location—cases that account for 2.80% of the sample—we impute values using temperature data from other households within the same district on that day. Additionally, we calculate relative humidity using the August-Roche-Magnus approximation following the guidelines of the US Environmental Protection Agency.[1]

For the main analysis, temperature is categorized into seven bins of 3°C increments: <12°C, 12–15°C, 15–18°C, 18–21°C, 21–24°C, 24–27°C, and >27°C. These bins are constructed using daily maximum temperature at the household's location. For each reference week, we count the number of days that fall into each temperature bin. These counts enter the regressions as explanatory variables, with the 18–21°C bin omitted as the reference category. Since the dependent variable is total weekly hours worked, the estimated coefficients are interpreted as the marginal effect, in weekly hours, of substituting one day in the reference bin (18–21°C) with one day in the corresponding temperature bin.

Precipitation We use precipitation data from two sources: the Peruvian Interpolated data of SENAMHI's Climatological and Hydrological Observations (SENAMHI PISCOp), developed by Aybar et al. (2019) and the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), developed by Funk et al. (2015). SENAMHI PISCOp provides monthly precipitation estimates on a 0.1×0.1 degree latitude-longitude grid, combining data from ground-based monitoring stations and CHIRPS. For robustness checks, we also incorporate monthly precipitation data from CHIRPS at a fine 0.05×0.05 degree resolution. It is important to note that SENAMHI PISCOp achieves its highest accuracy for the Pacific coast and the western flank of the Andes in Peru. To obtain daily rainfall estimates, we divide the monthly precipitation values by the number of days in the corresponding month.

[1] $\mathrm{RH} = 100 \times \left(\frac{\exp\left(\frac{17.625 \cdot \mathrm{TD}}{243.04+\mathrm{TD}}\right)}{\exp\left(\frac{17.625 \cdot \mathrm{T}}{243.04+\mathrm{T}}\right)} \right)$ where RH is the relative humidity in percent, TD is the dew point temperature (in °C), and T is the average temperature (in °C).

Daylight We calculate daily daylight hours for each weekday by measuring the difference between sunset and sunrise times at each household location. These times are derived using standard astronomical algorithms, based on the specific date each individual worked and the residential geographic coordinates provided in the ENAHO survey.

4 Empirical Approach

To examine the effect of temperature shocks on work time, we estimate the following baseline model using panel data with location and time fixed effects:

$$\mathrm{y}_{idt} = f(\beta, w_{it}) + \alpha_d + \lambda_t + \delta Z_{dt} + \theta X_{idt} + \varepsilon_{idt} \tag{1}$$

where the unit of observation is worker i in district d in year t. y_{idt} represents the labor outcome variable: total hours worked during the reference week of a given year. $f(\beta, w_{it})$ is a nonlinear function of temperature w_{it}, and β is the parameter of interest. Temperature is categorized into seven bins of 3°C increments. Bin 18-21°C serves as the reference category, as it falls within the human thermal 'comfort zone' of 18-22°C (Heal and Park, 2016), and it also corresponds to the average maximum temperature observed in our sample. β can then be interpreted as the effect on work hours of shifting a day with 18-21°C to a day with temperatures associated with bin j during the week. Note that the number of bins was selected so that each bin contains information for at least 10% of the sample. Robustness checks are conducted using alternative bin definitions. The model includes time fixed effects λ_t to control for seasonality—captured through year-month and weekly dummies—and district fixed effects α_d to account for time-invariant local characteristics. The error term ε_{idt}

is clustered at the region-month level to address temporal and spatial correlation in temperature. Additionally, we implement the standard error correction proposed by Conley (1999, 2010) using the algorithm developed by Colella et al. (2019). Our identification strategy relies on plausibly exogenous year-to-year variation in temperature within districts, allowing us to estimate whether individuals work more or fewer hours in relatively warmer years, conditional on location-specific and seasonal controls.

Although the baseline model reduces concerns about omitted variable bias (Deschenes and Greenstone, 2007), we include an additional set of controls, Z_{dt} capturing district-level weather conditions that may be correlated with temperature and independently influence working hours—specifically, rainfall, relative humidity, and daylight hours. We also include a vector of individual-level sociodemographic controls, X_{idt} which accounts for characteristics such as age, gender, rural residence, and the presence of dependents. As a robustness check, we replace X_{idt} with individual fixed effects to control for time-invariant unobserved heterogeneity at the individual level.

A potential concern with the baseline model is that the inclusion of fixed effects may absorb a substantial portion of the variation in weather, potentially leading to attenuation bias in the estimated temperature effects (Auffhammer et al., 2013). To assess this, we follow the approach used in previous studies (Guiteras, 2009; Fisher et al., 2012; Jessoe et al., 2016; Schwarz, 2018) and regress temperature on various combinations of fixed effects and time trends. The residuals from these regressions capture the remaining variation in temperature after accounting for fixed effects, providing a measure of the identifying variation available in our empirical strategy. Ideally, the remaining variation in temperature should be comparable in magnitude to the changes projected by climate change models. In this paper, we consider a benchmark scenario involving a predicted temperature increase of 1°C. Table A2 in the Appendix reports the R^2 from the regression, the standard deviation of the residuals, and the share of observations with residuals exceeding 1°C in absolute value. The remaining variation in weather is greater when using maximum temperature and when the model excludes individual fixed effects (see, for example, rows 7 and 21 in Table A2). Table A3 in the Appendix supports this conclusion, showing consistent results when each temperature bin is regressed on the various fixed effects specifications and time trends. These findings suggest that the data used in this study appears suitable for the baseline model in equation 1.

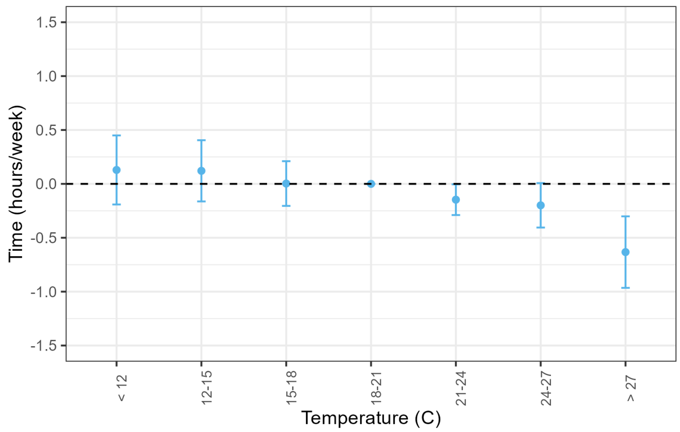
Finally, the empirical analysis leverages within-individual variation in working hours. Table A4 in the Appendix presents a decomposition of the standard deviation of work hours into between- and within-individual components, following (Kruger and Neugart, 2018). The results confirm that while there is meaningful variation in the labor data, the between-individual variation in work hours is larger than the within-individual variation.

5 Results

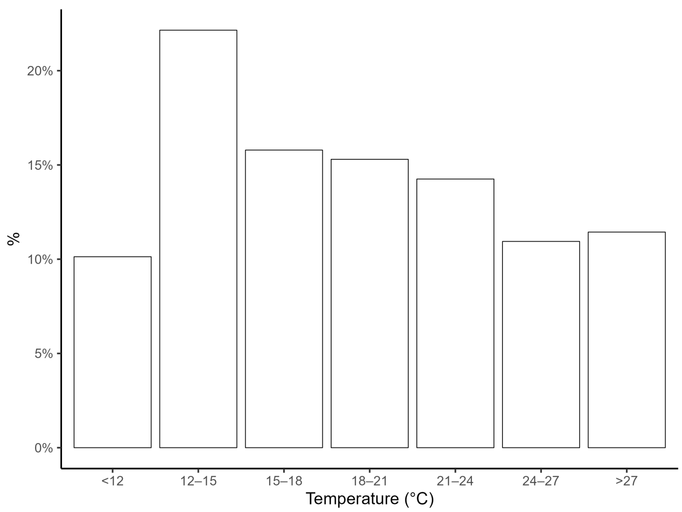
Figure 2 presents the main results from the baseline model. It plots the estimated effects on weekly work hours of replacing a day within the 18-21°C reference range with a day falling into a different temperature bin. The corresponding coefficient estimates and standard errors are reported in Column 1 of Table 1.

We find evidence that high temperatures negatively affect hours worked across the overall labor market. These results are consistent with findings from other developing countries, such as China, where, Garg et al. (2020) report that both extremely low and high temperatures reduce work hours. However, our findings differ from those in Mexico (Schwarz, 2018), South Africa (Gray et al., 2023), and the US (Zivin and Neidell, 2014). In the U.S. and South Africa, temperature appears to have no significant effect on aggregate work hours, while in Mexico, only low temperatures are associated with reductions in hours worked.

Figure 2: The Effects of Temperature on Work Time.



(a) Effects of temperature on hours worked



(b) Histogram for temperature bins

Note: Panel (a) shows the estimated effects of temperature on hours worked. Circles represent point estimates from regressions of total weekly working hours on temperature bins, controlling for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. Vertical lines indicate 95 percent confidence intervals, with standard errors clustered at the region-month level. Panel (b) shows the distribution of temperature for the corresponding temperature bins. The figure uses maximum temperature and ERA5 data for the period 2007-2015 and excludes observations from the jungle region.

The overall magnitude of the estimated temperature effects on hours worked is relatively modest. As shown in Figure 2 replacing a day within the 'comfort zone' temperature range (i.e., 18-21°C) with a day above 27°C is associated with a reduction of approximately 37.8 minutes (or 0.63 hours) of work time over the course of a week. This finding is consistent with observations from ILO (2019), which report that temperatures above 26°C impair work capacity. However, our estimate is smaller than the 1.2-hour weekly reduction reported for China over the same temperature range by Garg et al. (2020). One possible explanation for this discrepancy is Peru's higher rate of self-employment, which may allow for greater flexibility in adjusting work schedules in response to temperature fluctuations, thereby dampening the overall effect.

However, our estimated effects imply a non-negligible economic impact. To illustrate the potential aggregate implications, we combine our estimated reduction of 0.63 hours in labor supply with official 2017 statistics from the Central Reserve Bank of Peru and the National Institute of Statistics and Informatics. These include an employed population of 15,677,384 individuals, an average hourly labor income of 7 PEN, and a national GDP of 632,992 million PEN. A back-of-the-envelope calculation suggests that elevated temperatures could lead to a reduction in GDP of approximately 0.6%. Thus, while the estimated effect of 0.63 hours corresponds to a modest 1.45% decline in the average number of hours worked per week, its impact is distributed across millions of workers, resulting in aggregate economic losses that are economically significant.

Robustness checks Table 1 demonstrates the robustness of the main findings across a variety of model specifications. Column (1) reports the estimates from our baseline model, as specified in equation 1. In Column (2), we exclude workers in sectors where labor demand is more sensitive to temperature—namely, agriculture, forestry, fishing, and construction (Kruger and Neugart, 2018)—to address concerns that the observed effects may be driven by labor demand rather than labor supply. This concern is further mitigated by our focus on short-run, year-to-year variations, where changes in wages, employers, or employment contracts are less likely to occur (Connolly, 2008). Table A9, in the Appendix, presents additional evidence to mitigate this concern by directly adding demand conditions to the set of covariates, such as employment and unemployment rates, and regional GDP. Column (3) applies the spatial and temporal correlation correction proposed by Conley (1999, 2010) using the implementation developed by Colella et al. (2019). Column (4) clusters standard errors at the district level, which corresponds to the cross-sectional level of exogenous variation in temperature. In Column (5), we address potential residential sorting by excluding individuals who do not currently live in the district where they were born—under the assumption that individuals residing in their birth district remained there throughout the analysis period. Finally, Column (6) uses CHIRPS precipitation data in place of SENAMHI PISCOp to test the sensitivity of results to the choice of weather data source. Across all specifications, the estimated effects remain consistent in both magnitude and sign with the baseline model and are statistically significant, reinforcing the robustness of our findings.

Table 1 also reports results from alternative model specifications drawn from existing studies on temperature and work hours. Column (7) estimates a model with individual fixed effects in place of district fixed effects, following the approach of Garg et al. (2020). Column (8) includes individual fixed effects but omits controls for key weather-related variables—precipitation, relative humidity, and daylight hours—as in Schwarz (2018). When individual fixed effects are included (Columns 7 and 8), the main coefficients become statistically insignificant. This outcome reflects the limited within-individual variation in exposure to temperature shocks relative to the larger cross-sectional variation observed across districts. Consequently, part of the baseline estimates may be capturing between-subject rather than within-subject variation. Nonetheless, we contend that the estimated effects are not solely attributable to cross-sectional differences. As documented in Section 6, the results are driven by informal workers, whose heightened sensitivity to temperature shocks arises from structural vulnerabilities—such as greater caregiving responsibilities, larger numbers of dependents, and lower access to electricity—rather than from simple sorting across warmer versus cooler regions. Column (9) follows another specification from Schwarz (2018) controlling only for time fixed effects and individual demographics. All alternative specifications are replicated as closely as possible, and the resulting estimates remain broadly consistent in magnitude and direction with those from the baseline model.

We also estimate our baseline model using the full repeated cross-section sample from ENAHO, which includes all individuals—regardless of whether they are part of the panel. The results show qualitatively similar patterns: high temperatures are associated with significant reductions in work hours for informal workers, while the effect is not statistically significant for the overall population and becomes positive and significant for formal workers (see Table A8). These differences appear driven by changes in the composition of the sample, with a lower share of informal workers in the repeated cross-section. These findings confirm that the effects observed in the panel data hold more broadly across the labor force.

Tables A5 and A6 in the Appendix present robustness checks based on alternative temperature bin specifications. Table A5 reports results using nine bins with 3°C increments, while Table A6 uses narrower bins with 2°C increments. Across both specifications, the estimated effects remain consistent with those from the baseline model in terms of sign and magnitude, supporting the robustness of the main findings to alternative functional forms.

Table 1: Robustness Checks.

	Baseline	Demand	Conley S.E.	District S.E.	Sorting	Chirps	Model I	Model II	Model III
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Temperature (°C)									
< 12	0.13	0.23	0.13	0.13	0.18	0.12	-0.09	-0.07	0.01
	(0.16)	(0.32)	(0.22)	(0.22)	(0.21)	(0.16)	(0.27)	(0.26)	(0.21)
12-15	0.12	0.50*	0.12	0.12	0.13	0.12	-0.06	-0.03	0.02
	(0.14)	(0.25)	(0.20)	(0.20)	(0.18)	(0.14)	(0.25)	(0.24)	(0.20)
15-18	0.00	0.01	0.00	0.00	-0.01	0.00	0.00	0.04	-0.06
	(0.10)	(0.17)	(0.13)	(0.14)	(0.14)	(0.10)	(0.21)	(0.22)	(0.13)
21-24	-0.15**	-0.17*	-0.15**	-0.15*	-0.19*	-0.15**	-0.05	-0.04	-0.09
	(0.07)	(0.10)	(0.07)	(0.08)	(0.11)	(0.07)	(0.11)	(0.11)	(0.06)
24-27	-0.20*	-0.30*	-0.20**	-0.20**	-0.05	-0.20*	-0.07	-0.00	-0.08
	(0.10)	(0.15)	(0.09)	(0.10)	(0.14)	(0.10)	(0.20)	(0.18)	(0.08)
> 27	-0.63***	-0.74***	-0.63***	-0.63***	-0.51***	-0.63***	-0.28	-0.18	-0.42***
	(0.17)	(0.26)	(0.14)	(0.17)	(0.19)	(0.17)	(0.26)	(0.24)	(0.14)
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Relative Humidity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Daylight	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Individual FE	No	No	No	No	No	No	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean relative humidity (%)	75.52	76.66	75.52	75.52	74.15	75.52	75.43	73.88	75.52
N	113.392	53.029	113,392	113.392	64.687	113.392	102.501	102.501	113.392

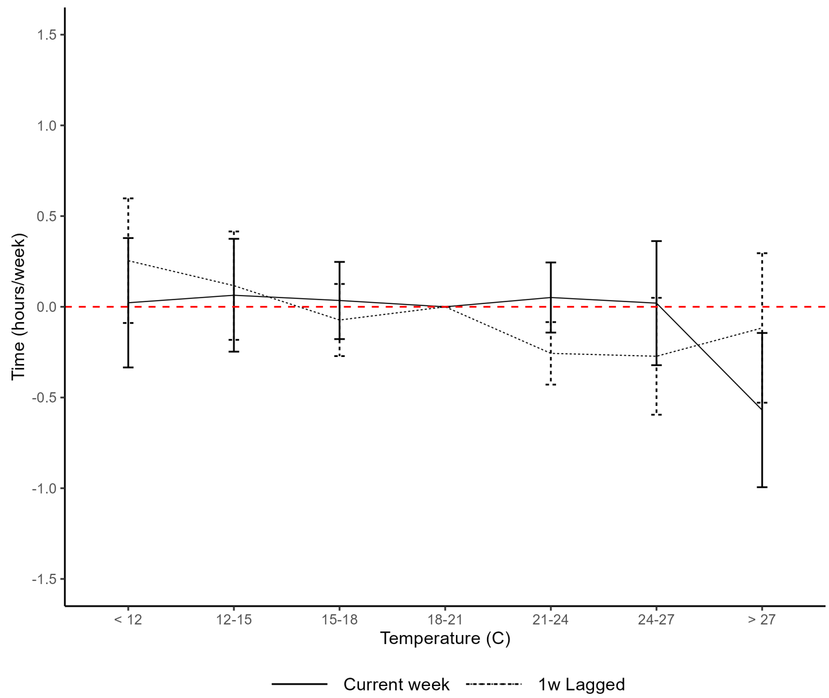
Note: This table reports estimated coefficients and standard errors from regressions of total weekly working hours on temperature bins for all workers. Column (1) presents the baseline model. Column (2) excludes workers in agriculture, forestry, fishing, and construction. Column (3) uses Conley standard errors to correct for spatial and temporal correlation. Column (4) clusters standard errors at the district level. Column (5) restricts the sample to individuals currently living in the district where they were born. Column (6) re-estimates the baseline model using CHIRPS precipitation data. Column (7) replicates the empirical model in Garg et al. (2020). Columns (8) and (9) replicate the specifications used in Schwarz (2018). Unless otherwise noted, standard errors (in parentheses) are clustered at the region-month level. For Columns (3), (4), (7), (8), and (9), standard errors are clustered at the district level. Statistical significance at the one, five, and ten percent levels is denoted by ***, **, and *, respectively.

Intertemporal Substitution We find no evidence of intertemporal substitution of work hours across adjacent weeks in response to high temperatures. This is illustrated in Figure 3, panel (a), where exposure to temperatures above 27°C is associated with a reduction in work hours during the same week (solid line). Similarly, high temperatures in the previous week are associated with lower work hours in the current week (dashed line), although this effect is not statistically significant. Panel (b) of Figure 3 shows the combined effects of contemporaneous and lagged exposure, with the estimate for temperatures above >27°C remaining negative and statistically significant. These findings suggest that workers are not shifting work hours across weeks in response to high temperatures. Therefore, the effects reported in Figure 2 are unlikely to be driven by intertemporal labor substitution and may reflect persistent, rather than temporary, impacts on labor supply.

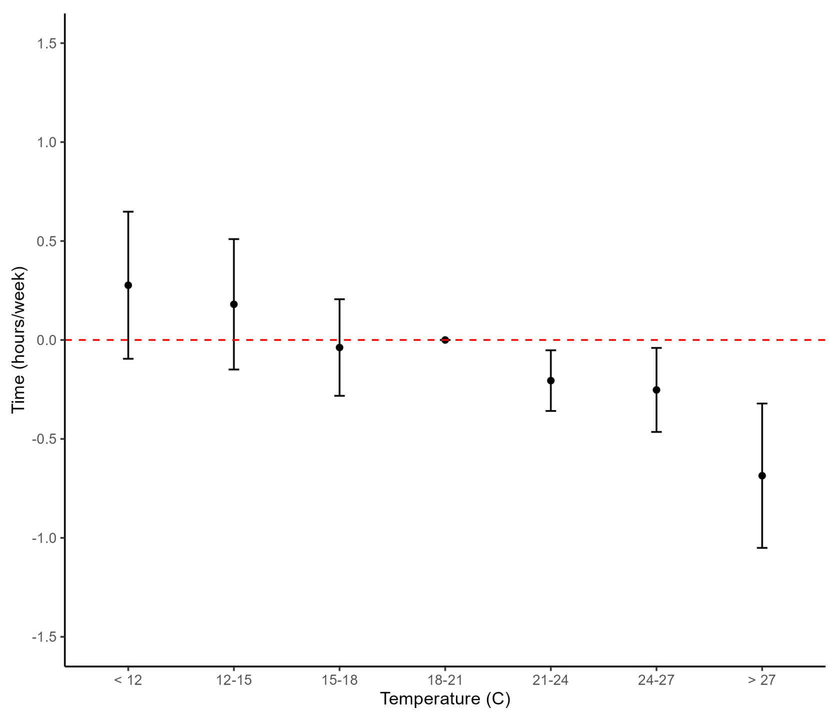
6 Discussion

Workers in informal employment appear to be the primary drivers of the negative effect of high temperatures on hours worked. A job is classified as informal if the production unit is not registered for tax purposes or if the worker is not covered by social security. Figure 4 illustrates the estimated effects of temperature on work hours for three groups: (i) all workers, (ii) informal workers, and (iii) formal workers. These estimates are obtained from separate regressions conducted for each group, rather than through interaction terms between temperature bins and a labor informality indicator. We tested whether the effects of the remaining control variables were equivalent across subgroups and found statistically significant differences. As a result, assuming homogeneity of control effects across groups—an assumption required when using interaction terms—does not appear appropriate in this context. The results in Figure 4 indicate that the overall negative effect observed in the baseline model is largely driven by informal workers.

Figure 3: Intertemporal Labor Substitution.



(a) Current and lagged effects of temperature

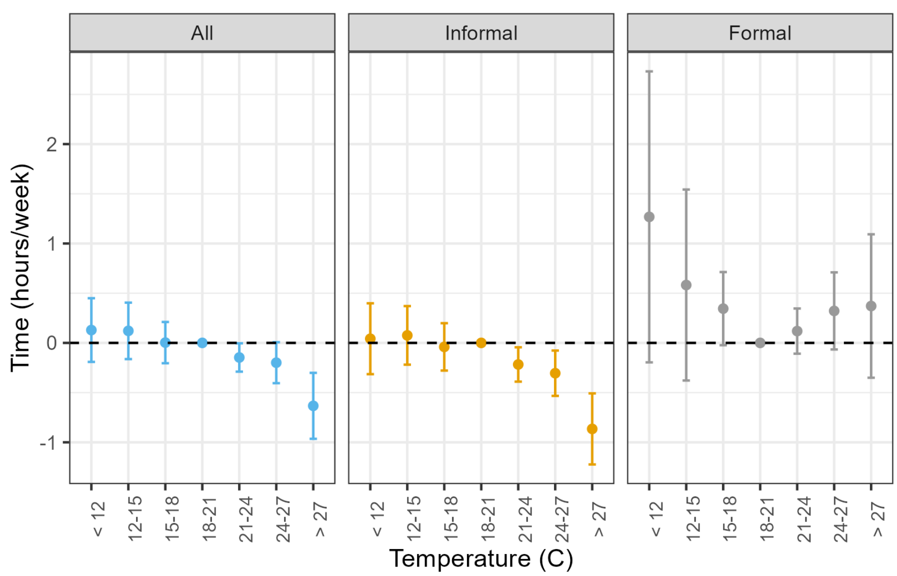


(b) Summation of current and lagged effects of temperature

Note: The figure shows estimated coefficients from regressions of weekly working hours on temperature bins for the current and previous weeks. Panel (a) plots the separate effects of contemporaneous and one-week-lagged temperature exposure. Panel (b) displays the combined (summed) effects across both weeks. All regressions control for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. Vertical lines represent 95 percent confidence intervals, with standard errors clustered at the region-month level. Estimates are based on daily maximum temperature using ERA5 data and exclude the jungle region.

However, whether a job is classified as formal may correlate with other factors that influence how temperature affects hours worked—such as access to air conditioning (AC) at work, job flexibility through self-employment, or vulnerability to demand shocks. In our sample, 60% of informal workers hold outdoor jobs—such as those in agriculture, fishing, mining, manufacturing, transportation, and utilities—where exposure to weather conditions is particularly high. Meanwhile, a study by the Ministry of Energy and Mines in Peru reports that 87% of government agencies do not use AC, and most private-sector firms also lack AC, with the exception of 44% of firms in the mining sector (MINEM, 2013). These findings suggest that limited access to AC at work is a common feature across both informal and formal employment.

Figure 4: The Effects of Temperature on Work Time.



Note: The figure shows estimated effects of temperature on total weekly working hours. Circles represent point estimates from regressions on temperature bins, controlling for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. Vertical lines indicate 95 percent confidence intervals, with standard errors clustered at the region-month level. Estimates are based on maximum temperature using ERA5 data, excluding observations from the jungle region.

It is important to note that many informal jobs are held by self-employed individuals who typically have greater flexibility in their work schedules. This suggests that informality may be correlated with job flexibility. However, we find no evidence that workers use this flexibility to shift work hours across weeks in response to temperature shocks. This result may be surprising, given that informal employment often allows for de facto flexibility. Yet, consistent with Kruger and Neugart (2018), our findings suggest that flexibility does not necessarily translate into intertemporal substitution of labor. Moreover, informal jobs may be particularly vulnerable to demand-side shocks—for instance, on hot days when people are more likely to stay indoors, reducing foot traffic and the number of customers served by informal workers. As a result, informal workers may need to adjust their hours in response to both supply- and demand-side shocks. Due to data limitations, however, we are unable to disentangle these mechanisms in the current analysis.

Informal vs. Outdoor One possible explanation relates to exposure to extreme temperatures, as informal workers are disproportionately employed in occupations that involve outdoor work. According to our data, 60% of informal workers are in outdoor-intensive industries—such as agriculture and construction—compared to 42% of formal workers (see Table A1 in the Appendix), a statistically significant difference. To disentangle whether the observed effects are driven by job informality or by outdoor exposure, we estimate separate regressions for four distinct groups: (i) informal outdoor workers, (ii) informal indoor workers, (iii) formal outdoor workers, and (iv) formal indoor workers. The results, presented in Figure 5, show that high temperatures negatively affect work hours for informal workers regardless of whether their jobs are performed indoors or outdoors. In contrast, we find no significant effect of temperature on work hours for formal workers in either setting. These findings suggest that occupational exposure alone cannot explain the differential impact, and that additional structural factors associated with informality likely drive the observed heterogeneity.

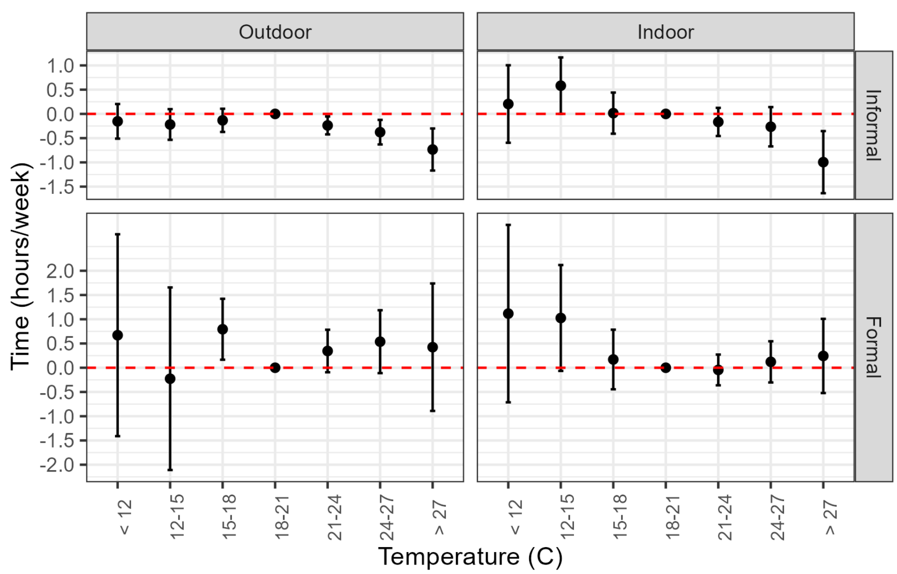
First, baseline climate conditions and local adaptation capacity may influence the magnitude of heat-related effects. Informal workers tend to live and work in cooler districts, with an average maximum temperature of 19.5°C and a minimum of 11.7°C, compared to 21.2°C and 14.7°C for formal workers, respectively—both differences are statistically significant (Table A1). As argued by Heyes and Saberian (2022), marginal effects of heat are often greater in cooler regions, due to lower local adaptation (i.e. populations and infrastructure are less adapted to extreme temperatures). Thus, the same level of heat stress may generate larger negative effects for informal workers who are less acclimated. One concern here may be that our results could be driven by cross-district differences among informal workers, rather than by genuine within-district responses to temperature shocks. If this were the case, we would expect informal workers in warmer districts to work fewer hours than those in cooler districts. However, descriptive evidence in Table A10 indicates the opposite pattern: on average, informal workers in warmer districts work more hours than their counterparts in cooler districts. This suggests that simple cross-sectional differences may not completely explain the negative coefficients in our baseline regressions.

Second, household structure and caregiving responsibilities can reduce the ability of informal workers to maintain a consistent labor supply during heat events. Informal workers are more likely to live in households with children (0.47 vs. 0.29), elderly members (0.08 vs. 0.06), and sick dependents (1.01 vs. 0.78),[2] all statistically significant differences. Moreover, they are more likely to be women (47% vs. 35%), who disproportionately carry the burden of caregiving. As shown in Das and Somanathan (2024), and Heyes and Saberian (2022), heat increases the likelihood of illness among both workers and dependents. Without access to paid leave or healthcare coverage, informal workers—particularly women—may be compelled to reduce work hours to meet caregiving needs exacerbated by heat exposure.

Third, differences in access to electricity contribute to disparities in heat resilience. Only

[2]We use the health module of the ENAHO survey to construct the number of dependent household members who reported an illness in the four weeks prior to the interview. This measure excludes chronic conditions and injuries resulting from accidents. A dependent is defined as a household member younger than 18 years old or older than 64 years old.

Figure 5: The Effects of Temperature on Work Time: Informal vs. Outdoor



Note: The figure shows estimated effects on hours worked from replacing a day within the reference temperature bin (18-21°C) with a day in another temperature bin during the working week. Outdoor jobs include occupations in high-exposure industries such as agriculture, fishing, mining, manufacturing, transportation, and utilities. Jobs are classified as informal if the production unit is not registered for tax purposes or if the worker is not covered by social security. Circles represent point estimates from regressions of total weekly working hours on temperature bins, controlling for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. Vertical lines indicate 95 percent confidence intervals, with standard errors clustered at the region-month level. Estimates are based on maximum temperature using ERA5 data and exclude observations from the jungle region.

88% of informal workers report having electricity at home, compared to 99% of formal workers (Table A1). Limited access to reliable electricity hinders the use of fans or cooling appliances, reducing the capacity of both workers and their dependents to cope with extreme heat. This lack of in-home adaptation not only exacerbates heat-related fatigue and sleep disruption among workers, increasing the likelihood of labor supply reductions on hot days, but also heightens the vulnerability of children, elderly members, and sick dependents, thereby increasing the likelihood that caregiving demands will translate into further labor supply reductions on hot days.

These findings suggest that job informality—rather than outdoor exposure—drives the negative impact of high temperatures on labor supply. While Zivin and Neidell (2014) report that high temperatures reduce hours worked in primarily outdoor industries in the U.S., our results indicate that, in the context of a highly segmented labor market such as Peru's, the distinction between indoor and outdoor work becomes less relevant. In such labor markets, informal workers are disproportionately vulnerable to temperature shocks, independent of their work environment.

7 Conclusion

This study examines the impact of temperature on working hours in Peru over the period 2007–2015. Using detailed worker-level and meteorological data, we find that high temperatures are associated with a reduction of 0.63 weekly hours worked. Other authors suggest that this effect may arise because working on hotter days becomes more physically demanding or less productive, or because warmer weather increases the relative appeal of leisure activities (Zivin and Neidell, 2014). However, our analysis further shows that the negative impact of high temperatures is driven by informal employment which is associated to household characteristics—such as limited access to electricity— and caregiving responsibilities, including the presence of more children, elderly members, sick dependents, and women within the household, which heighten the vulnerability of informal workers to heat exposure. Finally, we find no evidence of intertemporal labor substitution across weeks.

This paper leverages short-term variations in weather that exceed the projected long-term changes associated with climate change. By doing so, it aims to capture how working hours might respond as climate conditions evolve over time. However, interpreting these results requires caution, as they do not account for long-term behavioral adaptations that may become feasible in the future—or, conversely, for adaptation strategies currently available that may not be sustainable over time. As such, the short-run focus of this study does not fully reflect the gradual and complex nature of climate change and its long-term effects on labor supply. Future research should explore these behavioral responses in greater depth and develop improved methods for identifying workers exposed to outdoor conditions, as this group is particularly vulnerable to temperature shocks. Accurately characterizing this population is essential for understanding the broader impacts of climate change on labor markets. Additionally, future studies should incorporate modern big data sources to more precisely identify individuals' workplace locations and refine estimates of temperature shocks on time spent at work.

Competing interests:

The author declares none.

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APPENDIX

A Additional tables

Table A1. Summary Statistics.

	All (1)	**Informal** (2)	**Formal** (3)	**Outdoor** (4)	**Indoor** (5)	**Mean test** (2) vs. (3)
Hours (weekly)						
Main job	39.75	37.65	49.04	38.51	41.35	11.397***
Secondary job	15.84	16.18	13.34	16.65	14.69	-2.841***
All jobs	43.49	41.76	51.13	42.59	44.66	9.372***
Weather (average)						
Max Temperature (C)	19.83	19.50	21.28	18.93	21.00	1.776***
Min Temperature (C)	12.26	11.70	14.74	10.90	14.04	3.042***
Precipitation (mm)	30.88	35.19	11.80	39.97	19.01	-23.389***
Relative Humity (%)	75.52	75.14	77.21	74.72	76.56	2.069***
Daylight (hours)	12.10	12.10	12.08	12.10	12.10	-0.019***
Sociodemographics						
Age (years)	38.85	38.84	38.86	39.57	37.90	0.020***
Female	0.45	0.47	0.35	0.32	0.62	-0.128***
Spouse at home	0.77	0.78	0.75	0.81	0.72	-0.020***
Number of children	0.42	0.45	0.28	0.46	0.37	-0.169***
Percent over age 65	0.08	0.08	0.06	0.09	0.07	-0.021***
Rural	0.29	0.35	0.04	0.46	0.08	-0.312***
Access to electricity	0.90	0.88	0.99	0.84	0.98	0.116***
Outdoor	0.57	0.60	0.42	-	-	-0.182***
Frequency of sick dependents	0.97	1.01	0.78	-	-	-0.221***
N	113,392	98,347	15,045	73,001	40,391	

Note: This table reports the mean values of the main outcome variables and covariates for different subsamples. Column (1) includes all workers. Column (2) includes only workers in informal jobs, defined as those where the production unit is not registered for tax purposes or the worker is not covered by social security. Column (3) includes only formal workers. Column (4) restricts the sample to workers in high-risk industries, such as agriculture, fishing, mining, manufacturing, transportation, and utilities. Column (5) includes workers in all other industries not classified as high risk. Column (5) shows a mean test of differences between Column (2) and (3). A dependent is defined as a household member younger than 18 years old or older than 64 years old. Hours worked are reported for the reference week—the week prior to the interview. All weather variables are daily averages, except for precipitation, which is measured at the monthly level. All columns use ERA5 data and exclude observations from the jungle region.

Table A2. Temperature Variation under different Fixed Effects and Trends.

		Average Temperature (°C)			**Maximum Temperature (°C)**		
		R^2	σ_e	$\|e\| > 1$	R^2	σ_e	$\|e\| > 1$
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1	Constant		6.13	93.4%	0	5.90	89.9%
2	District FE	0.94	1.49	41.1%	0.93	1.56	44.1%
3	District FE, Linear Year	0.94	1.48	41.3%	0.93	1.56	44.2%
4	District FE, Quadratic Year	0.94	1.48	41.1%	0.93	1.56	44.1%
5	District FE, Cubic Year	0.94	1.47	40.8%	0.93	1.55	44.1%
6	Distict and Year FEs	0.94	1.46	40.5%	0.93	1.54	43.6%
7	District, Year and Month FEs	0.97	1.09	33.6%	0.95	1.33	42.9%
8	District, Year and Week FEs	0.97	1.08	33.0%	0.95	1.32	42.2%
9	Distict and Province*Year FEs	0.95	1.39	36.0%	0.94	1.46	38.9%
10	Distict, Province*Year and Province*Month FEs	0.99	0.62	10.0%	0.98	0.77	17.4%
11	Distict, Province*Year and Province*Week FEs	0.99	0.50	6.0%	0.99	0.64	11.2%
12	Distict, Year*Month and Province*Month Fes	0.99	0.64	10.9%	0.98	0.80	19.0%
13	Distict and Region*Year FEs	0.94	1.44	39.3%	0.93	1.51	42.1%
14	Distict, Region*Year and Region*Month FEs	0.98	0.80	17.0%	0.97	0.98	25.9%
15	Distict, Region*Year and Region*Week FEs	0.99	0.74	13.7%	0.98	0.92	22.4%
16	Distict, Year*Month and Region*Month FEs	0.98	0.78	16.0%	0.97	0.96	24.8%
17	Distict, Year and Region*Month FEs	0.98	0.84	19.7%	0.97	1.02	28.8%
18	Distict, Region*Year and Month FEs	0.97	1.05	32.0%	0.95	1.30	41.1%
19	Distict, Region*Year and Week FEs	0.97	1.04	31.5%	0.95	1.29	41.3%
20	Distict, Year*Month and Month FEs	0.97	1.04	32.1%	0.95	1.28	40.6%
21	Distict, Year*Month and Week FEs	0.97	1.03	31.1%	0.95	1.28	40.1%
22	Individual FE	0.98	0.62	19.5%	0.97	0.75	25.4%
23	Individual and Year and Month FEs	0.99	0.58	17.8%	0.98	0.72	23.9%
24	Individual and Region*Month and Year*Month FEs	0.99	0.51	15.4%	0.98	0.64	20.5%

Note: The table presents the remaining variation in temperature after controlling for various combinations of location and time fixed effects, as well as time trends. Columns (1) and (4) report the R^2 from regressions of temperature on these controls. Columns (2) and (5) report the standard deviation of the residuals, representing the remaining variation in temperature. Columns (3) and (6) indicate the proportion of observations with residuals exceeding 1°C in absolute value. Columns (1)–(3) use average temperature, while Columns (4)–(6) use maximum temperature.

Table A3. Temperature Bins Variation under different Fixed Effects and Trends.

		Maximum Temperature Bins (°C)						
		< 12	12-15	15-18	18-21	21-24	24-27	> 27
1	Constant	1.23	1.83	1.49	1.55	1.51	1.23	1.37
2	District FE	0.36	0.55	0.62	0.83	0.80	0.74	0.30
3	District FE, Linear Year	0.38	0.55	0.63	0.86	0.82	0.75	0.31
4	District FE, Quadratic Year	0.38	0.55	0.63	0.86	0.82	0.75	0.32
5	District FE, Cubic Year	0.40	0.56	0.63	0.85	0.82	0.75	0.33
6	Distict and Year FEs	0.42	0.56	0.64	0.87	0.84	0.76	0.34
7	District, Year and Month FEs	0.43	0.58	0.66	0.94	0.89	0.83	0.42
8	District, Year and Week FEs	0.44	0.59	0.66	0.94	0.90	0.84	0.43
9	Distict and Province*Year FEs	0.32	0.49	0.57	0.79	0.76	0.71	0.29
10	Distict, Province*Year and Province*Month FEs	0.29	0.43	0.49	0.51	0.51	0.40	0.17
11	Distict, Province*Year and Province*Week FEs	0.21	0.31	0.37	0.41	0.43	0.34	0.14
12	Distict, Year*Month and Province*Month Fes	0.40	0.52	0.56	0.57	0.60	0.45	0.23
13	Distict and Region*Year FEs	0.38	0.56	0.64	0.85	0.81	0.75	0.31
14	Distict, Region*Year and Region*Month FEs	0.37	0.55	0.61	0.64	0.66	0.52	0.24
15	Distict, Region*Year and Region*Week FEs	0.36	0.53	0.59	0.62	0.64	0.51	0.23
16	Distict, Year*Month and Region*Month FEs	0.43	0.57	0.62	0.67	0.72	0.56	0.28
17	Distict, Year and Region*Month FEs	0.41	0.55	0.61	0.66	0.69	0.54	0.26
18	Distict, Region*Year and Month FEs	0.41	0.58	0.65	0.93	0.88	0.83	0.41
19	Distict, Region*Year and Week FEs	0.42	0.59	0.66	0.93	0.89	0.84	0.42
20	Distict, Year*Month and Month FEs	0.46	0.59	0.66	0.94	0.91	0.84	0.43
21	Distict, Year*Month and Week FEs	0.46	0.60	0.66	0.94	0.91	0.84	0.43
22	Individual FE	0.27	0.41	0.41	0.38	0.37	0.27	0.12
23	Individual and Year and Month FEs	0.32	0.43	0.44	0.43	0.41	0.31	0.15
24	Individual and Region*Month and Year*Month FEs	0.35	0.45	0.45	0.43	0.44	0.31	0.17

Note: The table presents the residual variation in the number of days within each temperature bin after accounting for district fixed effects and other controls. For each bin, we regress the number of days on various combinations of location and time fixed effects. The absolute value of the residuals is then averaged across all observations, providing a measure of the variation remaining after removing systematic location- and time-specific components.

Table A4. Working Hours Variation.

	All **(1)**	***Informal*** **(2)**	***Formal*** **(3)**	***Outdoor*** **(4)**	***Indoor*** **(5)**
Between	18.49	18.55	18.60	17.32	21.58
Within	11.47	11.09	9.95	10.27	11.24

Note: The table presents the decomposition of the standard deviation of the main outcome variable—total weekly working hours—into between- and within-individual components. The decomposition is based on panel data and helps assess the relative contribution of cross-sectional versus time-series variation in explaining the overall variability in hours worked.

Table A5. The Effects of Temperature on Working Hours.

	All
Temperature (°C)	
< 9	0.30
	(0.27)
9-12	0.12
	(0.17)
12-15	0.12
	(0.15)
15-18	0.00
	(0.11)
21-24	-0.15*
	(0.08)
24-27	-0.20*
	(0.11)
27-30	-0.64***
	(0.17)
> 30	-0.61***
	(0.22)
N	113,392

Note: The table reports estimated coefficients and standard errors from a regression of total weekly working hours on temperature bins for all workers. The regression includes controls for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. The analysis uses daily maximum temperature from ERA5 data and excludes observations from the jungle region. Standard errors, reported in parentheses, are clustered at the region-month level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, ** and *, respectively.

Table A6. The Effects of Temperature on Working Hours - Narrow Bins.

	All
Temperature (°C)	
< 12	0.06
	(0.18)
12-14	0.19
	(0.16)
14-16	-0.07
	(0.14)
16-18	0.03
	(0.12)
20-22	0.02
	(0.07)
22-24	-0.09
	(0.09)
24-26	-0.09
	(0.12)
26-28	-0.23
	(0.16)
28-30	-0.41**
	(0.19)
> 30	-0.34
	(0.23)
N	113,392

Note: The table reports estimated coefficients and standard errors from a regression of total weekly working hours on narrower temperature bins for all workers. The regression controls for precipitation, humidity, daylight hours, sociodemographic characteristics, and location and time fixed effects. The analysis uses daily maximum temperature from ERA5 data and excludes observations from the jungle region. Standard errors, reported in parentheses, are clustered at the region-month level. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, ** and *, respectively.

Table A7. Number of households and individuals across years in our sample.

Number of years	**Individuals**	**Households**
(1)	**(2)**	**(3)**
2	34,309	7,970
3	36,938	6,600
4	22,696	3,244
5	18,283	2,393
6	1,166	144
Total	113,392	20,351

Note: This table presents the number of households and individuals across years in our sample. Column (1) shows the number of years we observe a household or individual. Column (2) shows the number of individuals observed in our panel sample. Column (3) shows the number of households observed in our panel sample.

Table A8. Baseline results using repeated cross-section sample 2007-2015.

	All	**Formal**	**Informal**
	(1)	**(2)**	**(3)**
Temperature (°C)			
< 12	0.14	-0.06	0.20*
	(0.13)	(0.18)	(0.11)
12-15	0.08	-0.10	0.16*
	(0.11)	(0.14)	(0.09)
15-18	0.02	-0.00	0.04
	(0.09)	(0.11)	(0.07)
21-24	0.01	0.05	-0.10*
	(0.03)	(0.05)	(0.06)
24-27	0.04	0.17**	-0.05
	(0.07)	(0.08)	(0.07)
> 27	-0.16	0.29**	-0.37***
	(0.11)	(0.12)	(0.12)
Precipitation	Yes	Yes	Yes
Relative Humidity	Yes	Yes	Yes
Daylight	Yes	Yes	Yes
Demographics	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
N	497,806	196,986	300,820

Note: This table presents estimated coefficients and standard errors from regressing total working on temperature bins using our baseline model and a repeated cross-section sample using all data available from 2007 to 2015. Column (1) considers all workers. Column (2) considers only workers with formal jobs. Column (3) considers only workers with informal jobs. Estimated standard errors, reported in parentheses, are clustered at the region-month level. Significance at the one, five and ten percent levels is indicated by ***, ** and *, respectively. All columns use ERA5 data and excludes the jungle.

Table A9. Baseline results and demand fluctuations.

	Baseline model			
	(1)	**(2)**	**(4)**	**(3)**
Temperature ($^\circ C$)				
< 12	0.13	0.13	0.14	0.14
	(0.16)	(0.16)	(0.16)	(0.16)
12-15	0.12	0.12	0.13	0.13
	(0.14)	(0.14)	(0.14)	(0.14)
15-18	0.00	0.00	0.01	0.01
	(0.11)	(0.11)	(0.10)	(0.10)
21-24	-0.15**	-0.15**	-0.15**	-0.15**
	(0.07)	(0.07)	(0.07)	(0.07)
24-27	-0.20*	-0.20*	-0.20*	-0.20*
	(0.10)	(0.10)	(0.10)	(0.10)
> 27	-0.63***	-0.63***	-0.63***	-0.63***
	(0.17)	(0.17)	(0.17)	(0.17)
GDP (district level)	Yes	Yes	Yes	Yes
Employment rate	Yes (district level)	Yes (district level)	Yes (region level)	
Unemployement rate	No	Yes (district level)	No	Yes (region level)
N	113,389	113,389	113,389	113,389

Note: This table presents estimated coefficients and standard errors from regressing total working hours on temperature bins using our baseline model for all workers. Column (1) includes the GDP and employment rate (employed population/working-age population) at the district level as additional covariates. Column (2) includes the GDP, employment rate (employed population/working-age population), and unemployment rate (unemployed population/economically active population) at the district level as additional covariates. Column (3) includes the GDP at the district level and employment rate at the regional level as additional covariates. Column (4) includes the GDP at the district level and employment and unemployment rates at the regional level as additional covariates. Estimated standard errors, reported in parentheses, are clustered at the region-month level. Employment and unemployment rates are calculated using ENAHO. GDP at the district level comes from (Seminario and Palomino, 2022). All columns control for precipitation, relative humidity, daylight hours, demographics, district and time fixed effects as in our baseline model. Significance at the one, five and ten percent levels is indicated by ***, ** and *, respectively. All columns use ERA5 data and exclude the jungle.

Table A10. Weekly hours worked by informal workers: cooler vs. warmer districts.

	Average weekly hours worked
A. Using daily average temperature	
Cooler districts	39.25
Warmer district	43.23
B. Using daily maximum temperature	
Cooler districts	39.39
Warmer district	42.92
N	98,347

Note: This table presents the average weekly hours worked by informal workers living either in cooler or warmer districts. Districts are categorized as cooler if their temperature is below the median of the sample. We use the daily mean temperature in Panel A and we use the daily maximum temperature in Panel B. All columns use ERA5 data and excludes the jungle.